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Steam flooding screening and EOR prediction by using clustering algorithm and data visualization

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STEAM FLOODING SCREENING AND EOR PREDICTION BY USING CLUSTERING ALGORITHM AND DATA VISUALIZATION

by

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ABSTRACT

Enhanced Oil Recovery (EOR) techniques are vitally important in the oil industry because these techniques could not only extend the life of wells, but also produce 10% to 30% additional oil from the reservoir. However, selecting the most suitable EOR techniques for unknown reservoirs is not easy for decision making. Based on literature, EOR screening criteria could help to find the best candidates for unknown projects, which is classified into two categories: conventional EOR screening and advanced EOR screening. In this research, an artificial intelligent (AI) method, hierarchical clustering algorithm, is adapted to analyze both steam flooding projects and worldwide EOR projects for the purpose of new steam flooding screening criteria and the prediction of EOR methods for unknown reservoir conditions.

Data pre-processing process were firstly conducted to ensure the data quality, then the hierarchical clustering algorithm was applied to the worldwide steam flooding projects and the worldwide EOR projects; after that the principal component analysis (PCA) was used to identify the major attributes in all clusters, and to visualize the projects in different clusters in a scatter plot by retaining high variance; and then descriptive statistics of using boxplot and scatter plot were utilized to establish the screening criteria for each cluster.

Three uniqueness were illustrated in this thesis. First, detailed screening criteria has been established based on the hierarchical clustering results. Second, categorical features (formation type) was considered as one of the impact factors for clustering, which none of the existing advanced screening criteria methods included. Third, dimensionality reduction techniques have been applied successfully which clusters are clearly laid out in a two dimensional scatter plot.

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TABLE OF CONTENTS

Page

LIST OF FIGURES

LIST OF TABLES

Page

NOMENCLATURE

Symbol	**Description**
AI	Artificial Intelligence
ANFIS	Adaptive Neuro Fuzzy Inference System
C	Conglomerate
CB	Combustion
CH	Chemical
CI	CO2 Immiscible
CM	CO2 Miscible
cP	Centipoise
D	Dolomite
EOR	Enhanced Oil Recovery
ES	Expert System
F	Fahrenheit
FL	Fuzzy Logic
ft	Foot
HI	Hydrocarbon Immiscible
HM	Hydrocarbon Miscible
HW	Hot Water
L	Limestone
MB	Microbial
mD	Millidarcy
MMP	Minimum Miscible Pressure

NI	Nitrogen Immiscible
NM	Nitrogen Miscible
NN	Neural Networks
PC	Principal Component
PCA	Principal Component Analysis
PO	Polymer
S	Sandstone
ST	Steam
SU	Surfactant
U	Unconsolidated Sandstone

1. INTRODUCTION

Enhanced Oil Recovery (abbreviated EOR) is the implementation of various techniques for increasing the amount of crude oil that can be extracted from an oil field [1]. Normally, by applying different EOR techniques into different oil field, additional 10% to 30% of crude oil could be produced from the reservoir. Therefore, EOR techniques are vitally important in the oil industry, and these techniques have been widely used around the world.

However, which EOR method is a good candidate for a specific reservoir is a hard question to most of the reservoir engineers and oil companies. To solve this problem, valuable EOR screening methods have been applied with the benefit of saving time for decision making, especially for mature reservoirs. These screening methods help reservoir engineers and companies to figure out the most suitable EOR method in a short time.

By far, there are mainly two different kinds of EOR screening methods. One is conventional EOR screening methods, which also been called "go/no-go" approach. In these methods, look-up tables are provided with different reservoir parameter intervals for each EOR method, and these look-up tables are coming from the analysis of the existing EOR projects (Alvarado 2010). Another method is called the advanced EOR screening methods. Artificial intelligence techniques, like neural network, fuzzy logic are implemented as tools to study the hidden knowledge of the data set, and these techniques are used to predict the best candidate of unknown new EOR projects.

The objectives of this research are to establish a new steam flooding screening criteria and to establish a novel framework for EOR prediction by implementing one of the artificial intelligence methods - clustering algorithms. Several tasks have been completed to fulfil these objective. The major processes for this research are shown in Figure 1.1, which includes data preparation, data mining, data analysis, dimensionality reduction for data visualization, and validation and prediction. All data were collected and cleaned either manually or using data mining techniques before using artificial intelligence techniques. Data were analyzed before and after the application of artificial intelligence techniques.

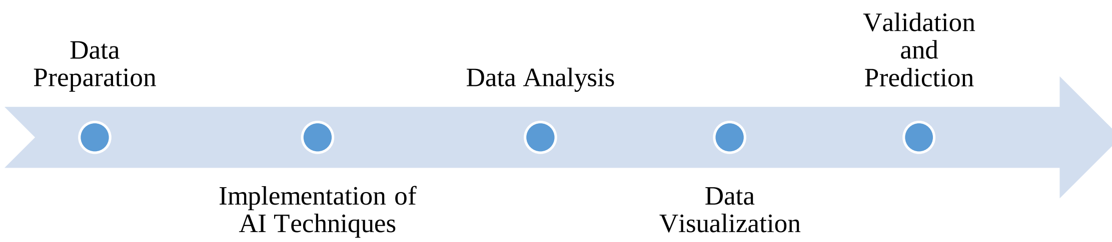


Figure 1.1. Flow chart of research

The rest of this thesis is organized into following sections. Section 2 is for literature review which summarizes the outcome of literature research; Section 3 presents data pre-processing, which includes both steam flooding data set and the worldwide EOR data set; Section 4 displays the methods used for data analysis, including the implementation of hierarchical clustering algorithms, descriptive statistics, and principal component analysis; Section 5 and 6 are the results get from the data analysis; the last section is the summary and conclusions of this research.

2. LITERATURE REVIEW

2.1. EOR METHODS

In the global context of growing energy needs and considering the depletion of oil and gas resources, extending the life of hydrocarbon reservoirs and improve the oil recovery will be a challenge for all petroleum engineers, especially for reservoir engineers. To improve the oil recovery, a number of methodological strategies have been developed over years, which called Enhanced Oil Recovery (EOR) methods. EOR methods refer to any techniques that could increase the recovery factor by the injection of materials which not normally presented in the reservoir, and it is generally classified into two categories: thermal methods and non–thermal methods, as shown in Figure 2.1. In the next few subsections, detailed introduction of EOR methods will be displayed.

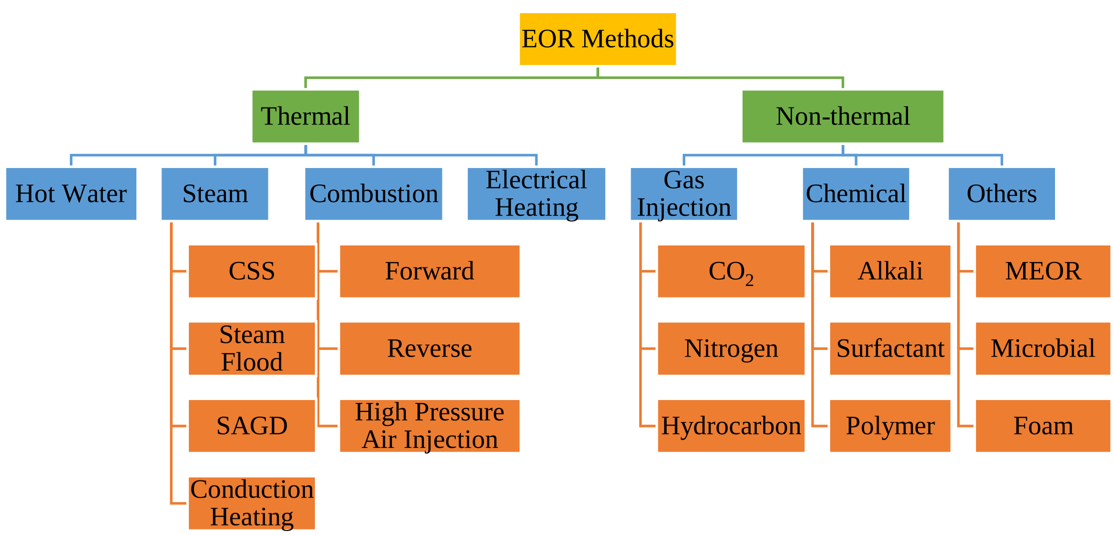


Figure 2.1. Classification of EOR methods. (Modified, Thomas 2008)

2.1.1. Thermal Methods. Thermal methods are made up of all the methods that could heat formations. The main mechanism of thermal methods is to increase the temperature of reservoir, which leads to the reduction of oil viscosity and the mobility ratio. Therefore, oil in the heated reservoir will be feasible to be displaced towards the production well. According to the Department of Energy, more than 40 percent of EOR projects in U.S. implemented the thermal techniques. Steam flooding and combustion are two primary types of thermal methods.

Steam flooding, sometimes called steam drive, is a process which steam is generated at the surface and being injected continuously into the reservoirs through injection wells. This method is most commonly used to enhance oil production and has a wide applications for light oil, heavy oil, deep reservoirs, and shallow reservoirs, etc. As illustrated in Figure 2.2, when steam enters the reservoir, it not only heats up the oil temperature which reduces the oil viscosity, but also provides the pressure to push heavy move towards production wells.

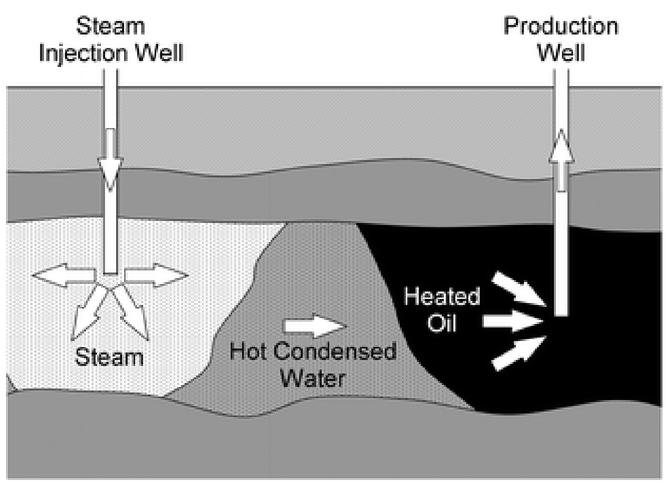


Figure 2.2. Steam flooding process [Amjad Sha, 2010]

Combustion, also called fire flooding, is the oldest thermal recovery techniques, and has been used for more than nine decades with many economically successful projects

(PetroWiki). The purpose of applying combustion techniques is similar to steam flooding, which is to heat the formation and reservoirs to reduce the oil viscosity, so the mobility ratio will drop down, and the oil will be easier to flow towards the production well. However, combustion method injects oxygen gases to burn the formation directly while steam flooding needs to be heated at the surface.

2.1.2. Non-thermal Methods. CO_2 Flooding techniques have been widely implemented worldwide especially in U.S. and Canada. From the Oil & Gas Biannually EOR Survey, 345 independent EOR projects have been using CO_2 flooding method, which occupies 46% of the total EOR projects. In United States, CO_2 flooding has been underway for more than 30 years, starting initially in the Permian Basin and have been expanding to several other regions of the country, particularly the Gulf Coast, Mid-Continent, and Rocky Mountains. The Department of Energy (DOE) has estimated that additional 240 billion barrels (38 km3) of oil could be recovered by the fully use of CO_2 flooding method. Moreover, DOE claims that the CO_2 flooding method is the ‘next generation’ of United States.

Figure 2.3 below depicts the process of CO_2 flooding. This process is a closed loop system, where it emerges with the oil separation at the surface, then recycled and re-injected into the formation. Usually, CO_2 is injected into developed oil field where it mixes with and produce the oil from the formation, thereby freeing it to move to production wells.

Chemical Flooding, is the injection of chemicals into the formation, mainly including polymer, alkaline, surfactant, polymer gels and combinations. The purpose of using polymer is to mix with water, which could increase the viscosity of water, and increase the sweep efficiency. Alkaline is mainly used to react with crude oil to generate soap, change the wettability and increase pH.

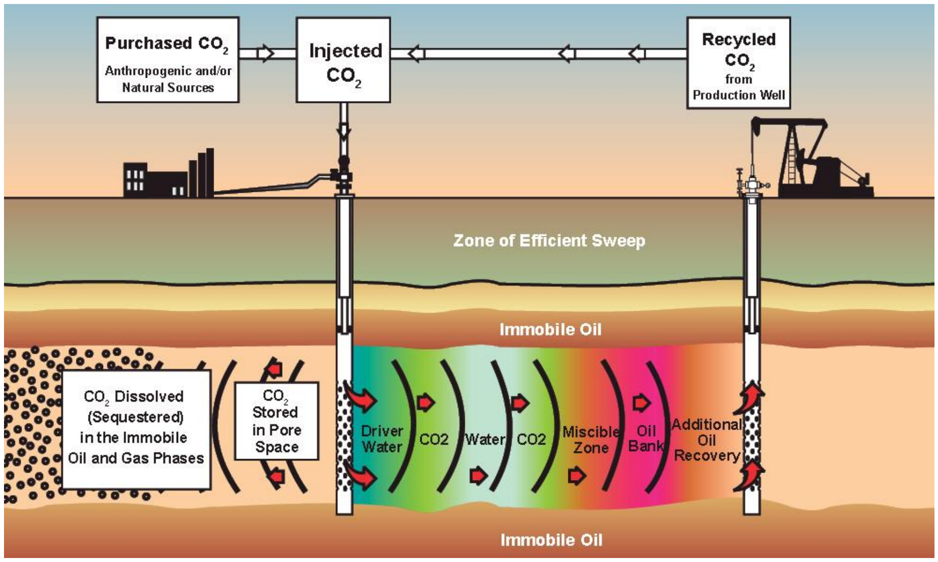


Figure 2.3. CO_2 flooding process [Reference 14]

Surfactants are used to lower the interfacial tension between the oil and water, and also change the wettability of the rock. Polymer gels are treating as blocking agent to diverting the flow, which usually used to block the high permeability zone, so the displacing fluids (water) goes to the low permeability zone and displace the oil in that area. Therefore, the overall sweep efficiency is increased.

2.2. EOR SCREENING METHODS

The idea of EOR screening methods have come to reservoir engineers' mind for a long time. In 1978, Poettman and Hause came up with the idea of micellar-polymer screening criteria and design, which is the first publication about EOR screening. After that, especially from the late 1990s', EOR screening criteria for broader EOR processes have been discussed by more researchers. For example, Taber et al. provided a look-up table in 1997 with 9 different EOR methods based on the field results and oil recovery mechanism;

Alvarado (2002) implemented the machine learning algorithms to draw the rules for screening; Al-Adasani (2010) updated the look-up table made by Taber (1997) based on 633 EOR projects collecting from 1988 to 2008 SPE publications; and Saleh (2014) updated the screening criteria for polymer flooding based on 481 oilfield projects.

The reason that researchers interest in studying EOR screening is because EOR screening is an effective and useful way to figure out the most suitable EOR methods for new EOR projects. For example, the life for a mature reservoir is really limited, EOR screening methods is a quick way to know the best candidates of EOR methods, which could help companies to save time for decision making, and save the operating costs.

EOR screening methods could be classified into two categories: conventional EOR screening and advanced EOR screening, detailed introductions and comparisons are laid out in the following subsections.

2.2.1. Conventional EOR Screening. The conventional EOR screening methods is also called 'go/no go' method, which generally use the ranges or intervals of reservoir parameters to filter out the best EOR candidates. Table 2.1 below is one of the well-known screening table about various EOR methods proposed by Taber et al. (1997). Nine important parameters were considered in the proposed screening process with suitable ranges, which are gravity, viscosity, composition, oil saturation, formation type, net thickness, average permeability, depth, and temperature.

Since the screening criteria table comes from the existing EOR projects and the expert knowledge, the screening criteria updates along with the dramatic increasing of the amount of existing EOR projects. In this case, the screening criteria has been modified to better present various EOR data set; namely, one method is only updating the ranges, another way is to add more important reservoir parameters to better pair with data set. For example, Hama (2014) and Saleh (2014) updated the screening criteria table for steam flooding and polymer flooding, respectively. They also came up with a complete framework for data cleaning. On the other hand, Bourdarot (2011) consider the potential ranges of MMP (Minimum Miscible Pressure) for various gas injectants (CO_2, hydrocarbon, N_2, H_2S), and he summarized all the methods for estimating the MMP.

Table 2.1. Summary of screening criteria for EOR methods (Taber et al. 1997)

		Oil Properties			Reservoir Characteristics					
Detail Table in Ref. 16	EOR Method	Gravity (°API)	Viscosity (cp)	Composition	Oil Saturation (% PV)	Formation Type	Net Thickness (ft)	Average Permeability (md)	Depth (ft)	Temperature (°F)
Gas Injection Methods (Miscible)										
1	Nitrogen and flue gas	> 35 ↗ 48 ↗	< 0.4 ↘ 0.2 ↘	High percent of C_1 to C_7	> 40 ↗ 75 ↗	Sandstone or carbonate	Thin unless dipping	NC	> 6,000	NC
2	Hydrocarbon	> 23 ↗ 41 ↗	< 3 ↘ 0.5 ↘	High percent of C_2 to C_7	> 30 ↗ 80 ↗	Sandstone or carbonate	Thin unless dipping	NC	> 4,000	NC
3	CO_2	> 22 ↗ 36 ↗ [a]	< 10 ↘ 1.5 ↘	High percent of C_5 to C_{12}	> 20 ↗ 55 ↗	Sandstone or carbonate	Wide range	NC	> 2,500[a]	NC
1–3	Immiscible gases	> 12	< 600	NC	> 35 ↗ 70 ↗	NC	NC if dipping and/or good vertical permeability	NC	> 1,800	NC
(Enhanced) Waterflooding										
4	Micellar/ Polymer, ASP, and Alkaline Flooding	> 20 ↗ 35 ↗	< 35 ↘ 13 ↘	Light, intermediate, some organic acids for alkaline floods	> 35 ↗ 53 ↗	Sandstone preferred	NC	> 10 ↗ 450 ↗	> 9,000 ↘ 3,250	> 200 ↘ 80
5	Polymer Flooding	> 15	< 150, > 10	NC	> 50 ↗ 80 ↗	Sandstone preferred	NC	> 10 ↗ 800 ↗ [b]	< 9,000	> 200 ↘ 140
Thermal/Mechanical										
6	Combustion	> 10 ↗ 16 → ?	< 5,000 ↓ 1,200	Some asphaltic components	> 50 ↗ 72 ↗	High-porosity sand/ sandstone	> 10	> 50 [c]	< 11,500 ↘ 3,500	> 100 ↗ 135
7	Steam	> 8 to 13.5 → ?	< 200,000 ↓ 4,700	NC	> 40 ↗ 66 ↗	High-porosity sand/ sandstone	> 20	> 200 ↗ 2,540 ↗ [d]	< 4,500 ↘ 1,500	NC
—	Surface mining	7 to 11	Zero cold flow	NC	> 8 wt% sand	Mineable tar sand	> 10 [e]	NC	> 3:1 overburden to sand ratio	NC

NC = not critical.
Underlined values represent the approximate mean or average for current field projects.
[a]See Table 3 of Ref. 16.
[b]> 3md from some carbonate reservoirs if the intent is to sweep only the fracture system.
[c]Transmissibility > 20 md-ft/cp
[d]Transmissibility > 50 md-ft/cp
[e]See depth.

2.2.2. Advanced EOR Screening. The advanced EOR screening includes all the methods that applies the Artificial Intelligence (AI) techniques to assist engineers to predict the most suitable EOR methods for new projects. Neural Networks (NN), Fuzzy Logic (FL), Machine Learning (ML), and Expert System (ES) are the common AI techniques that implemented in oil industry. For example, Alvarado (2002) proposed a methodology by utilizing the machine learning algorithm to draw the rules for EOR screening. Porosity, temperature, pressure, permeability, gravity, and viscosity are the six reservoir parameters that have been used for the algorithm. The results indicate that the EOR data set could be classified into six main clusters, and each cluster has its own rules for applications. Moreover, he also generated a 2D map by applying the space reduction techniques for the purpose of visualizing machine learning results.

2.2.3. Comparison of EOR Screening Methods. By comparing the conventional and advanced EOR screening methods, both screening methods are useful for EOR screening, and they both relies on the reservoir parameters gathered from field projects and the understanding of the characteristics, physics, and chemistry of each EOR projects (Manrique, 2007).

However, the conventional screening method is faster than the advanced method because users only need to go through the screening tables. In addition, the advanced method provides more accurate prediction results, such as the success probability of a certain EOR method.

Since the advanced EOR screening method involves more high techniques, screening methods involved with artificial intelligence techniques will lead the way to the future EOR screening. Therefore, in this research, complete frameworks for advanced steam flooding screening and EOR prediction by implementing hierarchical clustering algorithms has been established.

2.3. APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN OIL INDUSTRY

Artificial intelligence (AI) has a wide applications in oil industry in almost all research areas. For example, neural network and fuzzy logic have applications in the production area. The purposes of using these techniques are to predict the important performance indicators (Mohammadpoor 2012, Al-Amer et al. 2014), to optimize the integrate production system (Park 2006, Popa et al. 2005, Denney 2011, Cirilli et al. 2001), to monitoring and predicting production (Boomer 1995, Rebeschini et al. 2013, Ebrahimi 2010, Ramgulam et al. 2007, Popa et al. 2005), and also optimize the artificial lift systems (Bermudez et al. 2014, Mena et al. 1999).

Artificial intelligence also have numerous applications in well testing and well logging area. These AI techiniques are implemented for the purpose of well testing planning and interpretation (Stewart et al. 1989, Houze et al. 1992, Sung 1996, Aulia et al. 2014, Al-Kaabi et al. 1993), log correlation (Lim et al. 1998, 1999, Olea et al. 1986, and formation evaluation, which includes permeability, porosity, water saturation (Whittaker et al. 1986, Sitouah et al. 2013, 2014, Mohaghegh et al. 1995, Salazar et al. 2001, Anifowose et al. 2012).

There are also a great number of applications in the reservoir engineering. AI could help to predict bottom-hole pressure (Osman et al. 2005), reservoir characterization (Kumar 2012, Anifowose et al. 2012), and identify analogous reservoirs (Perez-Valiente et al. 2014).

Since the scope of this thesis is about EOR projects, we summarized all applications of AI in EOR area, as shown in Table 2.2 below. Sayyad et al. (2013) implemented the Adaptive Neural Network - Particle Swarm Optimization (ANN-PSO) to predict the

Minimal Miscible Pressure (MMP) for CO_2 flooding projects by using 9 reservoir parameters, which are reservoir temperatures, mole percentage of oil components, molecular weights of the heavy fraction (C_5+), and mole percentage of the non- CO_2 components (Cl, N_2, H_2S, and C_2-C_4) in the injected gas. Alikhani (2011) uses Adaptive Neuro Fuzzy Inference System (ANFIS) to predict the ultimate oil recovery for microbial method by using porosity, permeability, salinity, temperature, pressure, and pH. Siena (2015), Alvarado (2002), and Babushkina (2013) all use the same physical reservoir parameters (porosity, permeability, depth, temperature, gravity, viscosity) in the whole EOR data set, but the purpose of using clustering algorithm are different. In Siena's paper, Bayesian Hierarchical Clustering Algorithm was implemented to predict EOR methods for unknown EOR projects and the Principal Component Analysis (PCA) was used for the purpose of data visualization. Alvarado used the machine learning for the same intention to predict EOR methods, but he used a 2D map to present his results. Moreover, Babushkina uses K-means and Hierarchical Agglomerative Clustering Algorithm to predict the oil recovery.

Table 2.2. Artificial intelligence applications in EOR research area

Publications	**EOR Methods**	**Applications**	**Artificial Intelligence Algorithms**	**Input Parameters**
Sayyad, H., et al. (2013)	CO2 flooding	Predict MMP	ANN-PSO	Reservoir Temperature, Mole Percentage of Oil Components, Molecular Weights of the Heavy Fraction (C_5+), Mole Percentage of the Non-CO_2 components (Cl, N_2, H_2S, and C_2-C_4) in the injected gas

Table 2.2. Artificial intelligence applications in EOR research area (cont.)

Alikhani, P., et al. (2011)	Microbial	Predict Oil Recovery	Adaptive Neuro Fuzzy Inference System (ANFIS)	Porosity, Permeability, Salinity, Temperature, Pressure, pH
Siena, M., et al. (2015)	All EOR	Forecasting EOR potential	Bayesian Hierarchical Clustering Algorithm	Porosity, Permeability, Depth, Temperature, Gravity, Viscosity
Alvarado, V., et at. (2002)	All EOR	Predict EOR Methods	Machine Learning	Porosity, Permeability, Depth, Temperature, Gravity, Viscosity
Babushkina, E. V. (2013)	All EOR	Multi-dimensional interpolation of recovery factor	K-means and Hierarchical Agglomerative Clustering Algorithm	Porosity, Permeability, Depth, Temperature, Gravity, Viscosity

3. DATA PRE-PROCESSING

As mentioned in literature review section, the agglomerative hierarchical clustering algorithm has been implemented for both steam flooding projects and the whole EOR data set collected from the biannually EOR survey from the *Oil and Gas Journal*. Before implementing clustering algorithms into these data set, data preprocessing procedures need to be taken for duplicate elimination, missing data prediction and senseless data erasing. With refined data, analysis can be operated in order to decide how the data can be used.

3.1. RAW DATA

The steam flooding data set is collected from 1980 to 2012 Biannually EOR Survey from the *Oil and Gas Journal*. Eight reservoir parameters were selected for data analysis, including one categorical feature and seven numerical features. The categorical feature is the formation type, and the numerical feature are porosity, permeability, depth, viscosity, API gravity, temperature, and oil saturation before steam flooding, as shown in Table 3.1. The reason for selecting these properties to build up our data set is because they are the main reservoir properties that could describe reservoirs, and these properties are commonly used for EOR projects data analysis.

Table 3.1. Features of steam flooding projects

Properties	**Features**
Formation Type	Categorical
Porosity	Numerical
Permeability	Numerical
Depth	Numerical
API Gravity	Numerical
Viscosity	Numerical
Temperature	Numerical
Oil Saturation, start	Numerical

For the whole EOR projects, all the data were collected from the biannually EOR survey from the Oil and Gas Journal from 1998 to 2012. Eighteen reservoir parameters were utilized for data preparation, including two categorical features and sixteen numerical features, as shown in Table 3.2. The two categorical features are the EOR methods and formation type. Besides all the numerical features used in steam flooding projects, the whole EOR projects add one extra feature into selection, which is the oil saturation after the utilization of EOR techniques, and each numerical features have both minimum and maximum values.

Table 3.2. Features of whole EOR projects

Properties	**Features**
EOR Methods	Categorical
Formation Type	Categorical
Porosity (min, max)	Numerical
Permeability (min, max)	Numerical
Depth (min, max)	Numerical
API Gravity (min, max)	Numerical
Viscosity (min, max)	Numerical
Temperature (min, max)	Numerical
Oil Saturation, start (min, max)	Numerical
Oil Saturation, end (min, max)	Numerical

3.2. DATA QUALITY CONTROL METHODS

Data quality is important for data analysis. Having the most comprehensive and up to date information could help to ensure that the analyzing result is correct and useful. For the established data sets, three problems were concerned: duplicate data, missing data, and senseless data. For both data sets, we applied the same methods to improve the quality of the data sets.

3.2.1. Duplicate Data. Duplicate data were the first problem that been concerned during data pre-processing process. Two types of duplicate data were observed. One is the data that is exactly the, another is the data that has slightly different records among the projects. Before analyze the data sets, this problem has to be solved to avoid the redundancy of information, and the biased results. For example, for the worldwide EOR data set, the data collected includes various EOR methods, like steam flooding, polymer flooding, CO_2 miscible flooding, if the data sets have duplicate projects, the percentage of the number of each EOR method will be incorrect. Moreover, in the EOR data prediction part, the success percentage of each EOR method in each cluster will be inaccurate (e.g. change the success percentage of steam flooding from 20% to 50%), which not only leads to the wrong results, but also may change the results of decision making among the selection of EOR methods for unknown projects.

To avoid the problems caused by the duplicate data, a series actions has been conducted, as shown in Figure 3.1. Firstly, the duplicate projects were deleted if projects are with the exact same records. Then for the data with little different records, two different cases were under consideration. If the difference is caused by the missing values in the project and the other values remain the same, project with missing values were deleted. If projects that have just one feature different, the comparison of irrelevant information between projects were conducted (like report year, project locations). If the irrelevant information are the same, the projects were considered as repeating projects; if they have different irrelevant information, the reservoir properties and fluid properties might coincidentally be the same. Therefore, projects with different irrelevant information were kept in the data sets.

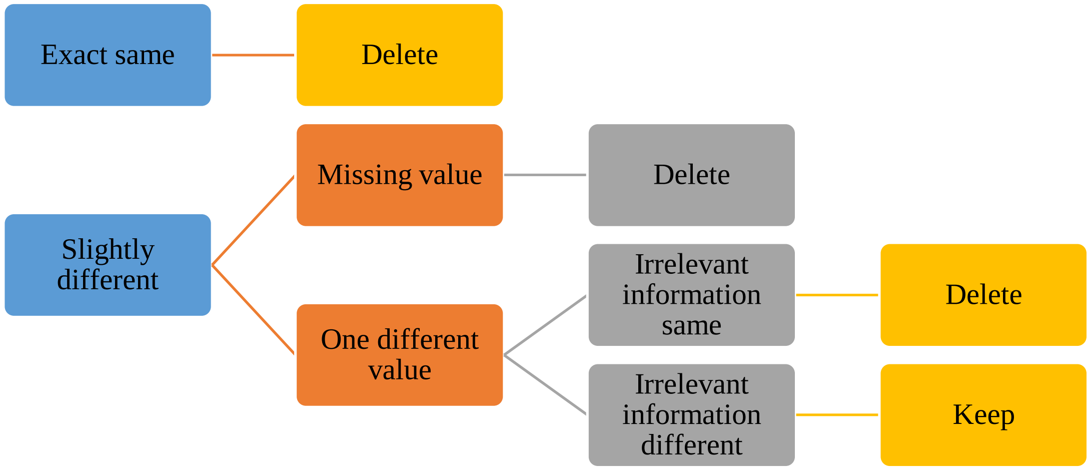


Figure 3.1. Decision processes with duplicate data

3.2.2. Missing Data. Missing data is a common problem in a data set. Since the hierarchical clustering algorithm and the principal component analysis algorithm cannot analyze the projects with missing values, projects with missing values should either to be imputed or delete the whole projects with missing values. Both methods have pros and cons. For imputation, it could help to keep as many projects as possible, but may lead to the biased results (single imputation). However, if the projects with missing data are ignored or deleted, even though data within the data set are real and not biased, it may shorten the size of the data set dramatically. Therefore, choosing appropriate methods dealing with missing data is not an easy decision to make, and it needs a lot of future studies.

In this research, to dealing with this problem, single imputation (mode) were utilized for numerical data, and projects were deleted if any selected categorical feature(s) is not available.

3.2.3. Senseless and Inconsistent Data. Data which is abnormal or does not make sense were considered as a sort of senseless. For example, it is impossible to have an EOR projects under the condition of 0 °F, or with 0 °API. In this case, all zeros in the data sets are treated as missing data, and they were processed as the methods used for missing values.

Inconsistent data is another problem that have been found in the data sets. For the categorical features, like the formation type, the combination of dolomite and tripolitic chert were recorded into several format; for the numerical features, especially for saturations, some of the value were recorded decimals (0.3), and some of them are in percentage (30%). To improve the quality of data sets, all data were changed into a certain format to keep the consistence.

3.3. CLEANED DATA SETS AND STATISTICS

After pre-processed the steam flooding projects, 409 projects were retained, and the formation type distributions are illustrated in Figure 3.2. Sandstone and unconsolidated sand are the most common types for steam flooding projects, which sandstone occupies 88% among all the projects, and unconsolidated sandstone formation type takes 10%.

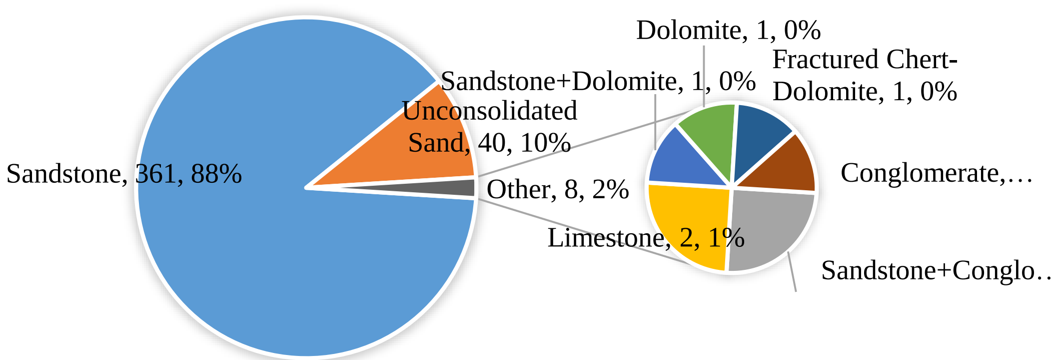


Figure 3.2. Pie chart of formation type distributions for steam flooding projects (from 1980 to 2012 Oil and Gas Journal)

For worldwide EOR projects data set, after the data pre-processing process, 726 EOR projects remained in total, which includes thirteen different EOR methods (Steam flooding, CO_2 miscible flooding, CO_2 immiscible flooding, hydrocarbon miscible flooding, hydrocarbon immiscible flooding, polymer flooding, nitrogen miscible flooding, nitrogen immiscible flooding, microbial, hot water, surfactant flooding, chemical flooding, and combustion.) and seven formation types (sandstone, dolomite, limestone, tripolitic, unconsolidated sandstone, shale, and conglomerate). Figure 3.3 and Figure 3.4 present the distribution of different EOR projects and the distribution of formation types.

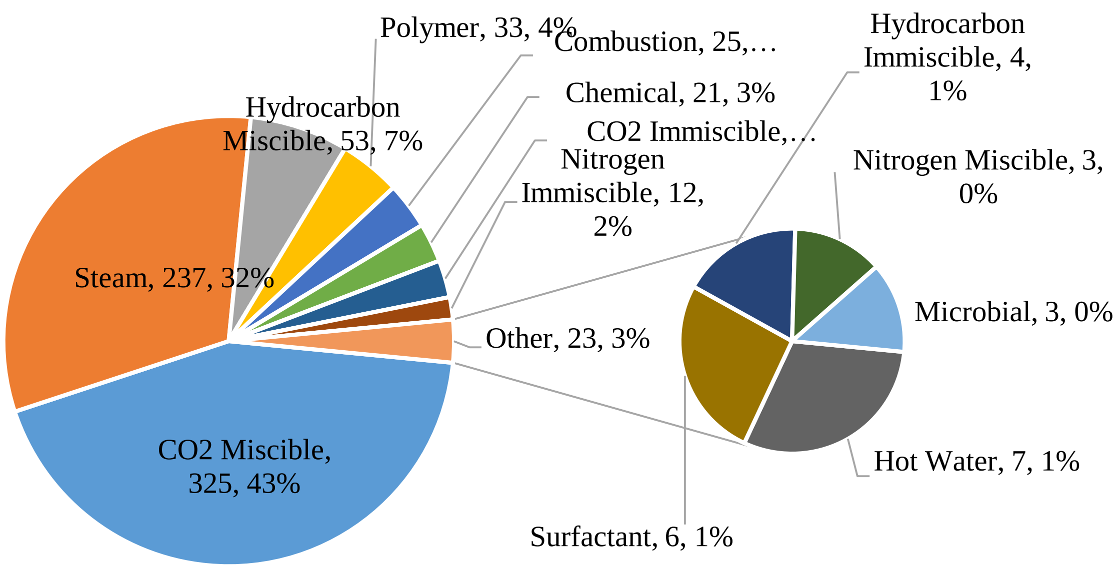


Figure 3.3. Project distributions of EOR methods (from 1996 to 2012 Oil and Gas Journal)

As illustrated in Figure 3.3, CO_2 miscible flooding and steam flooding are the two most popular EOR methods, which has 325 projects and 237 projects, respectively, and occupies 75 % of the overall EOR projects in total. For the formation type which shown in Figure 3.4, in contrast with the steam flooding projects, the overall EOR projects are mainly with the formation type of sandstone and carbonate (dolomite and limestone), which takes 49% and 37% of all the projects, respectively, and not many projects with shale, conglomerate, unconsolidated sand formation type EOR projects were reported in the *Oil and Gas Journal* EOR Survey.

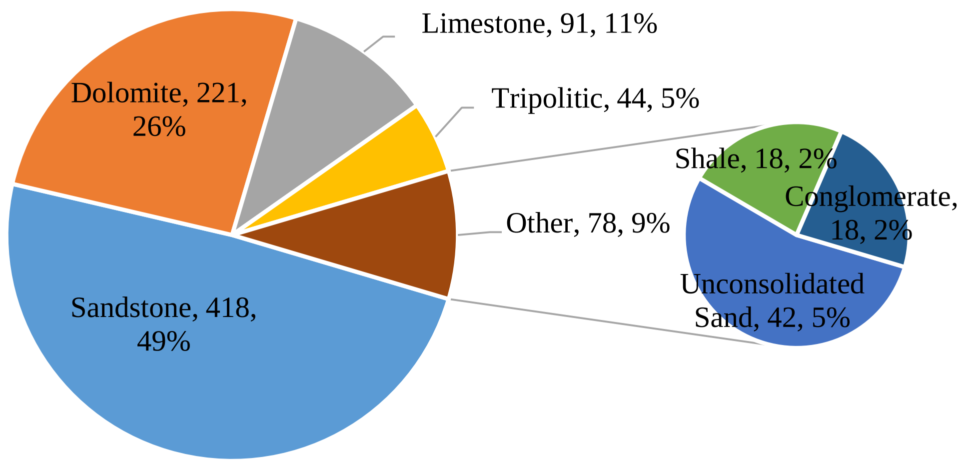


Figure 3.4. Project distributions of formation type for worldwide EOR projects (from 1996 to 2012 Oil and Gas Journal)

4. DATA ANALYSIS METHODS

After data preparation, hierarchical clustering analysis, descriptive statistics, and principal component analysis were utilized to reveal the hidden relationships among projects; to characterize the clusters; and to visualize the results and to figuring out the governing features in the data sets.

Figure 4.1 is the workflow of data analysis process. Hierarchical clustering algorithms were implemented to study the hidden knowledge in the data sets. The results of this process are dendrograms and clusters which could show the distances and grouping results among projects. Within a cluster, projects are similar with each other, which share the similar characteristics.

Figure 4.1. Workflow of data analysis process

In order to reveal the characteristics of each cluster, descriptive statistics approach comes to the stage for data analysis. Correlation coefficient are used to study the relationships among reservoir properties; statistical graphics, like box plots and bar charts are generated to know the property ranges; and descriptive statistical summaries are used to show the statistical results.

Last but not least, principal component algorithms are also implemented in the clustering results to visualize the results and filter out the dominating reservoir properties in the data sets. Mono plots are generated to not only indicates the relationships of reservoir properties, but also presents the most import factors in the data sets; scatter plots are used to show the relationship of projects in a 2D map. The following subsections briefly describe these computational and visualization techniques.

4.1. HIERARCHICAL CLUSTERING ANALYSIS

Hierarchical clustering is a method of cluster analysis in data mining, which groups data with a sequence of nested partitions, either from singleton clusters to a cluster including all individuals or vice versa (Xu, Wunsch, 2010). This method is generally divided into two types: agglomerative hierarchical clustering and divisive hierarchical clustering. Figure 4.2 below illustrates the difference between these two clustering. Agglomerative hierarchical clustering is a 'bottom up' method where each observation represents as an individual cluster at the beginning, two clusters are then merged in each step until all objects are forced into the same group. Divisive hierarchical clustering is a 'top down' method where all observations start in one cluster, and splits are performed recursively as one moves down the hierarchy (Reference 16). For this research, the agglomerative hierarchical clustering was used.

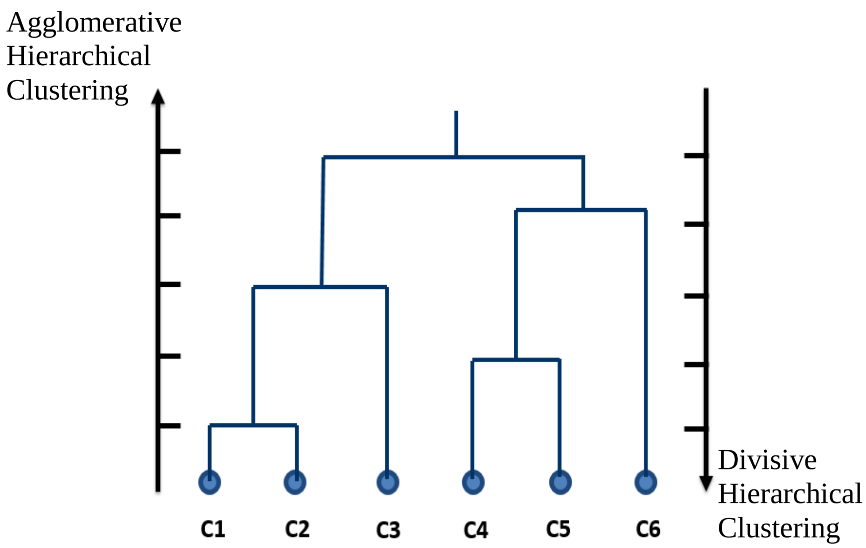


Figure 4.2. Hierarchical clustering

Agglomerative clustering starts with N clusters, each of which includes exactly one data point. The conduction of merge operation is determined by the computation of distance, which represents the similarities and dissimilarities among clusters. If the distance between two clusters is the shortest, they will merge into a bigger cluster.

In other words, data points within the same cluster are similar to one another, and dissimilar to the data points in other clusters. The greater the similarity or homogeneity within a group and the greater the difference between groups is, the better or more distinct the clusters are. The general agglomerative clustering can be summarized by the following procedure, which is also summarized in Figure 4.3.

There are three main reasons why the clustering algorithm was implemented in the oil industry. First, data set are typically multi-dimensional, it is difficult to know their similarities or relationships. Secondly, by utilizing the clustering algorithm, it is easy to characterize the data after clusters are formed, which means the hidden knowledge and characteristics could be revealed. Last but not least, cluster results provide more information about the data set compared with the ranges, and this makes the results more accurate and reliable.

As mentioned previously, distance is important because it determines how clusters merged each other. In this research, the Manhattan Distance for numerical features dues to this method is commonly used, which is defined as:

$$\mathrm{d(p,q)} = |\mathrm{a1_{x1}} - \mathrm{a1_{x2}}| + |\mathrm{a2_{x1}} - \mathrm{a2_{x2}}| + |\mathrm{a3_{x1}} - \mathrm{a3_{x2}}| + \ldots + |\mathrm{an_{x1}} - \mathrm{an_{x2}}|$$

and the distance for categorical feature between p and q is:

$$d(p,q) = \begin{cases} 1 & if\ AND(p,q) = 0 \\ 0 & otherwise \end{cases}$$

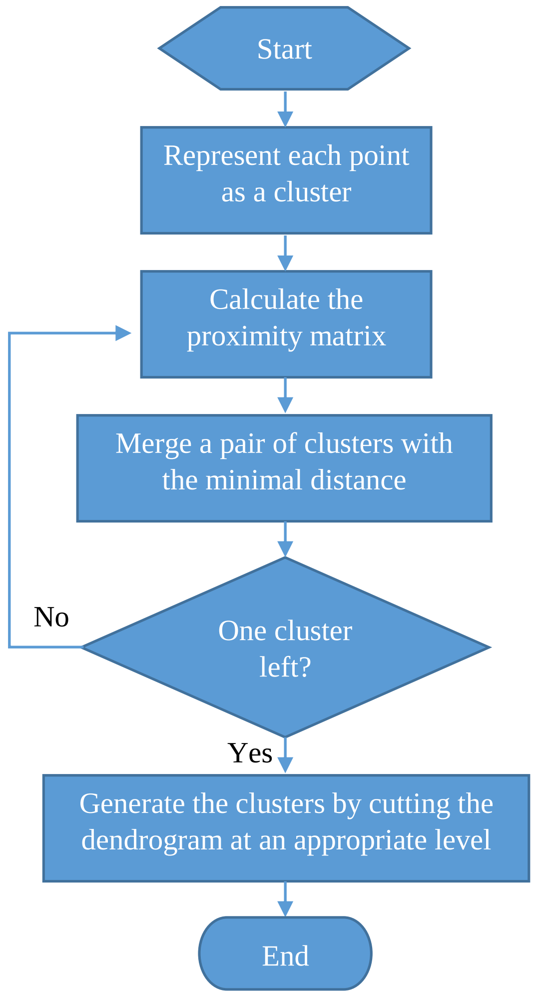


Figure 4.3. Flowchart of the agglomerative hierarchical clustering algorithm. (Rui Xu and Donald C. Wunsch II, 2010) [Reference 17]

After the computation of the Manhattan Distances the distance of each numerical feature was normalized from 0 to 1 to pair with the distance calculated in categorical features, and to ensure that all the features are equally weighted. Moreover, the weighted average linkage was utilized to define the distance function between two clusters.

Another important task is the determination of clustering levels. In this research, the clustering output for both steam flooding and EOR data sets stops at clustering level 20 with dendrograms. With these dendrograms, cluster stability analysis is studied to filter out the outliers and the main clusters. Therefore, by analyzing the stability of clusters, clustering level could be determined.

4.2. DESCRIPTIVE STATISTICS

When analyzing reservoir parameters, scatter plots in correlation coefficients can quickly uncover patterns, and reduce large amount of data to a subset of interesting relationships. Correlation describes the strength the relationship between two variables, correlation coefficient ranges from -1 to 1. 1 indicates a perfect positive linear relationship and -1 in the case indicates perfect negative linear relationship. 0 indicates that variables are uncorrelated, and there is no linear relationship. Normally, the correlation coefficient lies between these values.

Figure 4.4 below illustrates the concepts. The top two rows present the linear relationships between two variables, and the bottom row indicates the non-linear relationships, which are in different shapes.

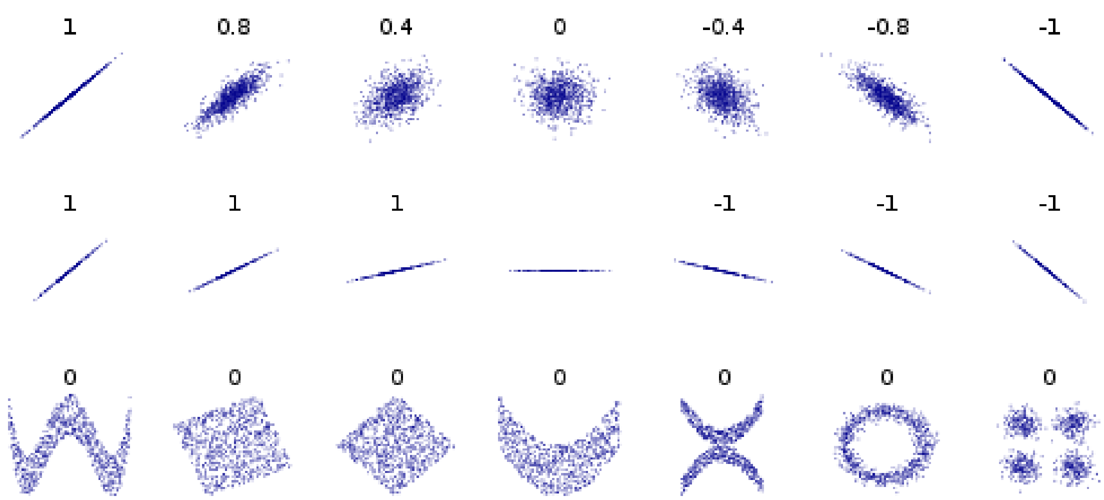


Figure 4.4. Correlation coefficient [Reference 50]

In this research, the Pearson's Correlation Coefficient has been used to measure the strength of the association between the two properties. The modified effects of different Pearson's Correlation Coefficients (r) are shown in Figure 4.5 (Reference 57). For r falls into the range of -0.3 to +0.3, it means the two properties are not very related to each other; for r from ±0.3 to ±0.5, it shows that the properties are relatively related; and for r equal or greater than ±0.5, it indicates that the two properties are strongly related.

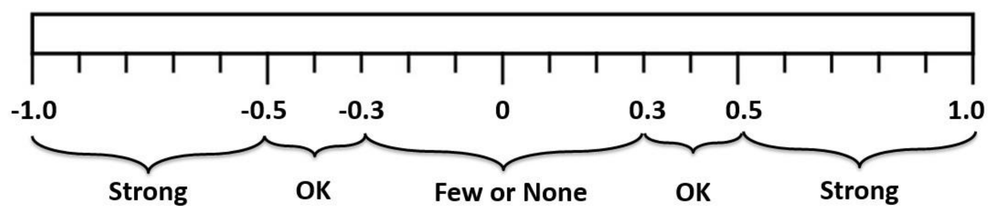


Figure 4.5. Effects of different Pearson's Correlation Coefficients [modified, Reference 57]

4.3. PRINCIPAL COMPONENT ANALYSIS

In this research, Principal Component Analysis (PCA) were implemented for the following purposes: 1) to figure out the dominating factors (reservoir parameters) in the data set; and 2) to present the clustering result in a 2D map, which helps to understand the relationships between clusters and the EOR projects.

4.3.1. Principal Component Analysis. In order to understand the theory behind the PCA method, a simple example is given and shown in Figure 4.6a. For a two-dimensional (2D) data set, if one dimensional is the goal to achieve, in another word, reduce from two dimensional to one dimensional, a projection line will be needed to represent the data (as the red line shown in Figure 4.6b). If the original data were projected onto a red line, green points could be get as shown in Figure 4.6c, and the distance between each point and the projected version is pretty small. Figure 4.6d displays the lower dimensional (1D) results after the dimensionality reduction. The projection line could represents the locations of the each data point with the minimized variance reduction in the original data set.

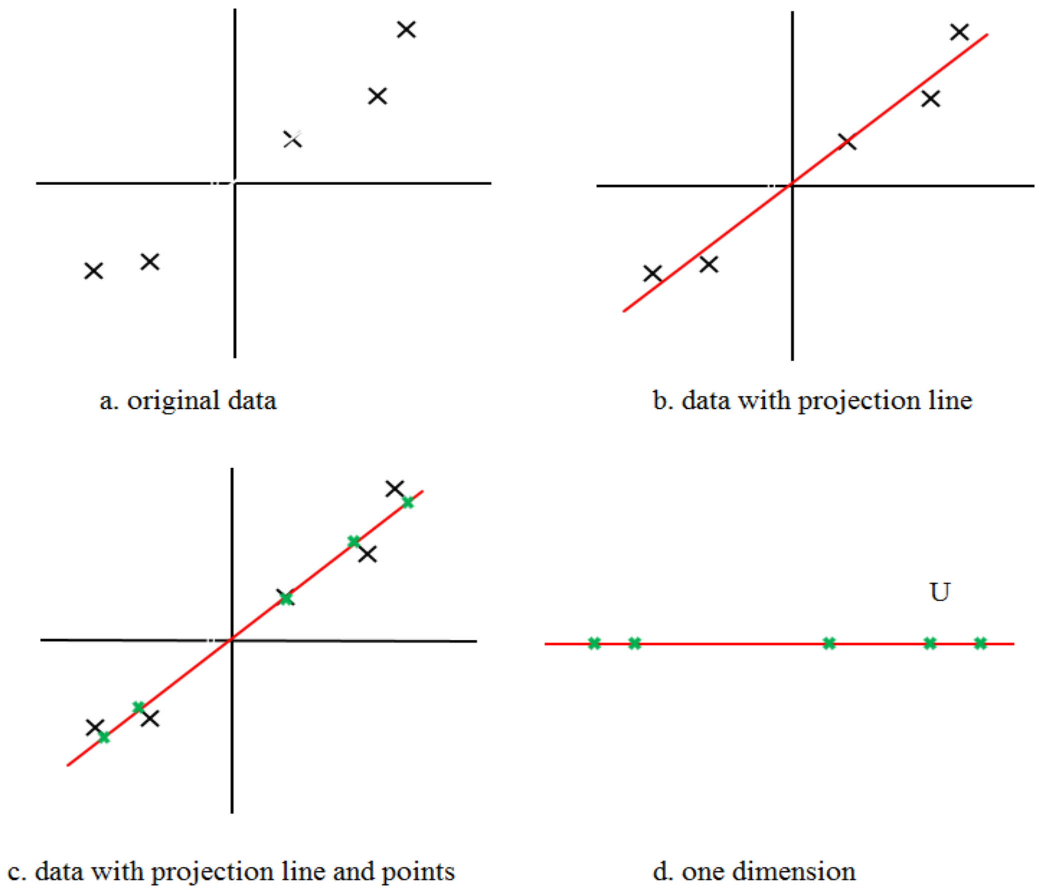


Figure 4.6. Dimensionality reduction example

Therefore, the PCA method finds a lower dimensional surface (from 2D to 1D in this case) to project the data. In other words, PCA is a method that find the minimized sum of squares of distance between original data and the projected points. The distance between original data and the projected point is called the projection error. In a general case, for a n dimensional data set, any dimensions (k) could be achieve by implementing PCA if n>k>2.

4.3.2. Principal Component Analysis Procedures. In this subsection, the procedures for PCA is presented to help better understand the how to use PCA for a real project, especially for the steam flooding and worldwide EOR projects, which includes data pre-processing, implementation, choosing the number of principal components, and the visualization with mono plot.

Step 1. Data Pre-processing for PCA. It is always important to perform mean normalization, and then depending on the data, maybe perform feature scaling as well. Data should be prepared without missing data, duplicate data, and inconsistent data as mentioned in section 3.

Step 2. Implementation of PCA. After finishing data pre-processing, PCA were implemented. Take Figure 4.6 as an example (from 2D to 1D), there are mainly two things what PCA does. The first one is PCA helps to find the projection line (red line), the second thing is it helps to compute the numbers or the locations of the projection data on the red line. In another case, if a two dimensional data is the goal to achieve from a three dimensional data set, what PCA does is it firstly find the 2D plane with the minimum sum square of distance between the original data and the projection plane, then it needs to calculate the location of projection points in the 2D plane.

Step 3. Choosing the number of principal components. For a n dimensional data set, a n principal components will be got, which contains the 100% of the information of the original data. However, to reduce the dimensions, not all principal components need to be utilized. Usually, a PCA algorithm should retain about 90% of the variance for a good result after dimensionality reduction, therefore, the number of principal components could be determined.

In this research, the agglomerative hierarchical clustering algorithm was implemented for both the steam flooding projects and the whole EOR data set. Seven important reservoir parameters were selected for steam flooding projects, and sixteen variables for the whole EOR data set. So multi-dimensional data sets (seven dimensional and sixteen dimensional) need to be presented in a two dimensional or three dimensional in order to visualize and better present our data. Meanwhile, 90% of the variance should be retained.

Step 4. Visualization using mono plot. A two dimensional correlation mono plot of the first two principal components can visualize the relationships between variables, as shown in Figure 4.7. The correlation mono plot shows vectors pointing away from the origin to represent the original variables. The angle between two vectors is an approximation of the correlation between the variables. A small angle indicates the variables are positively correlated, and angle of 90 degrees indicates the variables are not correlated, and an angle close to 180 degrees indicates the variables are negatively correlated. The length for the line and how it closes to the circle indicates how well the variable is represented in the plot.

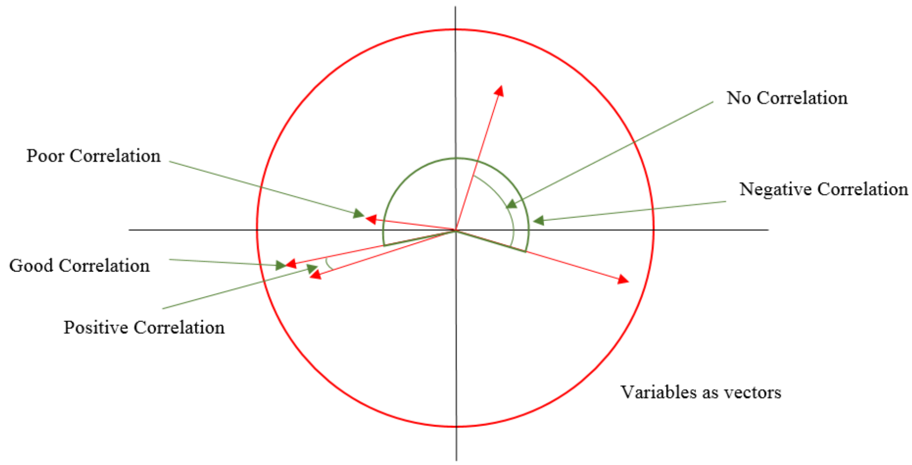


Figure 4.7. Mono plot explanations

5. RESULTS FROM STEAM FLOODING DATA SET

In this section, the results of the hierarchical clustering analysis, descriptive statistics, and the principal component analysis are displayed for the steam flooding projects.

5.1. HIERARCHICAL CLUSTERING RESULTS

After the implementation of hierarchical clustering algorithm, 20 clusters were achieved. Figure 5.1 is the compact visualization of the results, and Figure 5.2 indicates the detailed clustering results of clustering level 20.

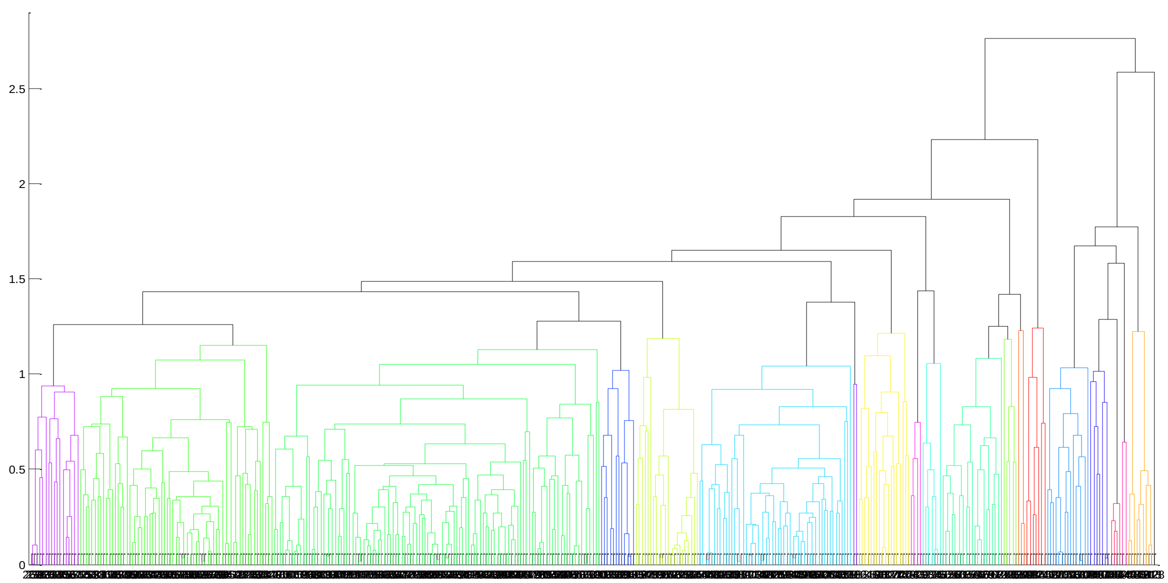


Figure 5.1. Steam flooding clustering results (from 1980 to 2012 Oil and Gas Journal)

The horizontal axis in Figure 5.1 represents clusters, and the vertical axis indicates the distance between clusters. With the process of clusters merge, the distance between clusters are greater, which means clusters are more dissimilar.

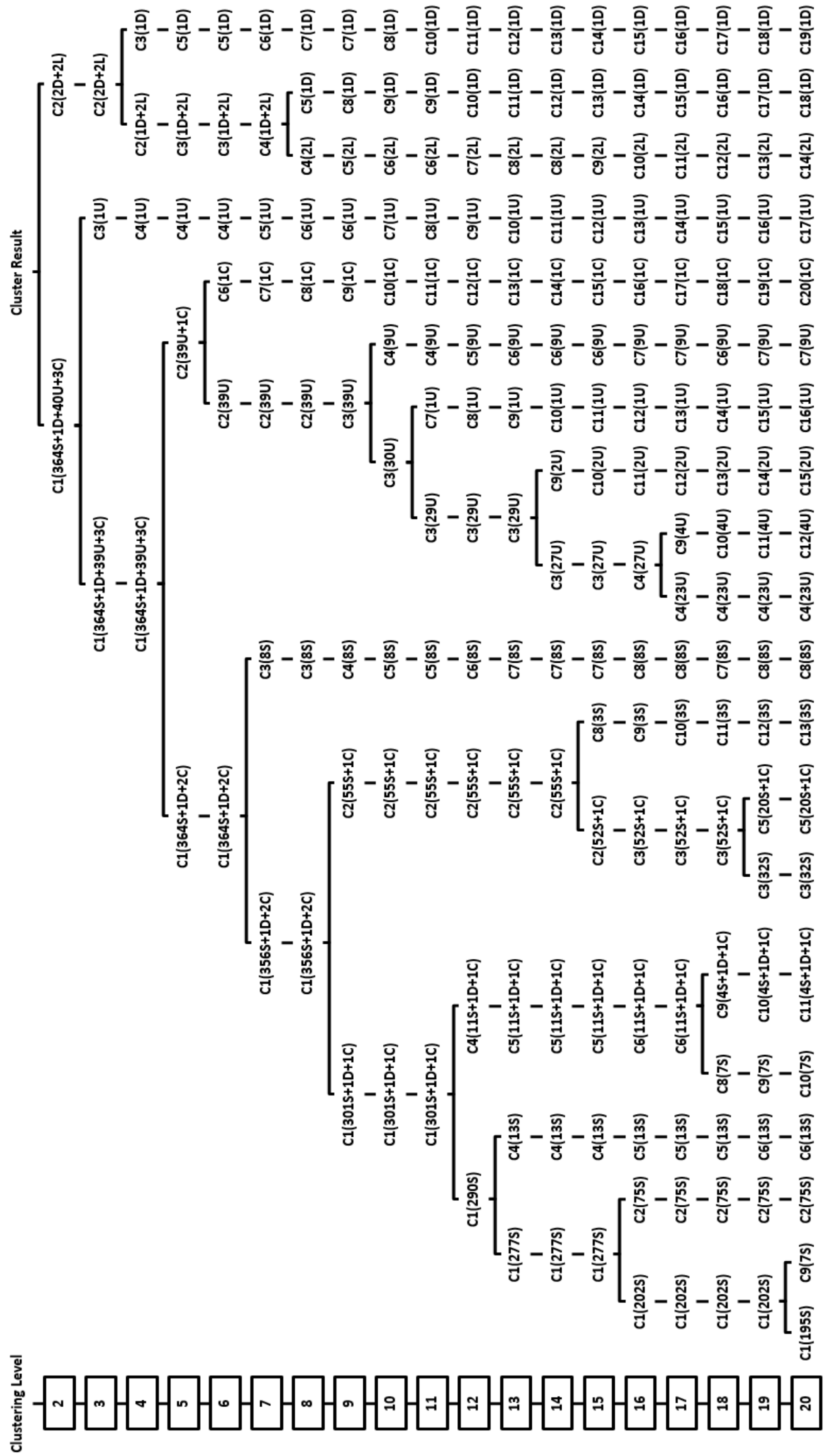


Figure 5.2. Hierarchical clustering results using hierarchical level of 20

As seen from the dendrogram in Figure 5.2, the hierarchy structure of all the steam flooding data is clearly laid out. Each element in the dendrogram represents the hierarchical clustering result at each clustering level. In this dendrogram, S stands for sandstone formation, D represents dolomite formation, U indicates the unconsolidated sandstone formation, C is the conglomerate formation, and L is the limestone formation. Figure 5.3 is the expressions of one cluster from cluster level 9. C1 (301S+1D+1C) represents the name of this cluster is called cluster 1, and it is the biggest cluster in this level. This cluster includes 301 records with sandstone formation type, 1 record of dolomite formation, and 1 record of conglomerate formation.

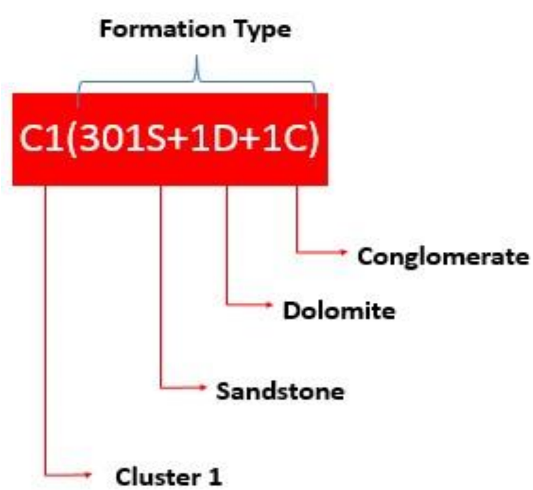


Figure 5.3. Expression of the Cluster 1 in cluster level 9

Since the agglomerative hierarchical clustering algorithm were used as indicated before, this dendrogram is a bottom-up structure, which starts at the bottom of the dendrogram and treat each project as an individual cluster. Clusters are merged each other into a bigger cluster at each clustering level by compute and compare the distances until all the projects were formed into the same cluster. In other words, clusters with similar characteristics are tend to merge earlier in the dendrogram, vice versa.

As illustrated in the dendrogram, all the elements are well distributed based on the formation type. Moreover, on the right side of the dendrogram, cluster 17 and cluster 19 formed a quite stabled cluster during the hierarchical clustering process. In this case, cluster 17 and cluster 19 represents were considered as outliers in the data set because they are dissimilar with other clusters so that they are not able to merge with other clusters.

In order to get better understanding of each specific cluster and to study the characteristics for each cluster, the domain knowledge of steam flooding and range for each properties are applied as shown in Table 5.1 based on the study of steam flooding projects data set and the common knowledge for steam flooding.

Table 5.1. Domain knowledge for steam flooding

Property	**Category**	**Average value range**
Oil viscosity (cp)	High	≥5000
	Medium	[1000, 5000]
	Low	<1000
Formation porosity (%)	High	[25,50]
	Low	<25
Formation permeability (md)	High	≥ 5000
	Intermediate high	[1000, 5000]
	Intermediate low	[100, 1000]
	Low	<100
Formation depth (ft)	Deep	≥ 3000
	Intermediate deep	[1000, 3000]
	Intermediate shallow	[500, 1000]
	shallow	<500

Table 5.1. Domain knowledge for steam flooding (cont.)

Formation temperature (ºF)	High	≥ 250
	Medium	[100, 250]
	Low	[45, 100]
Oil saturation before steam flooding (%)	High	[70, 100]
	Medium	[30, 70]
	Low	<30

From the dendrogram, the hierarchy structure is very obvious, and each cluster represents one type of the formation type, which means formation type is an important feature that determines whether or not clusters merge into a bigger cluster. Meanwhile, since the formation type was the only categorical feature in the data set, the boundary domain of each formation type is very obvious, and it is easy to identify the difference between compositions of formations. While other numerical features or properties are set into a rough range rather than a specific precise number. Therefore, the formation type is a good indicator for clustering, and the formation type was utilized to study the main characteristics of each cluster. Figure 5.4 and Figure 5.5 below present the characteristics of clusters for sandstone and unconsolidated sandstone, respectively.

In construction of these two diagrams below, small clusters having only one record each or those with the sandstone formation having less than 5 records are considered special clusters. They are analyzed separately. As the two branch charts illustrated, each branch clearly present the characteristics of one cluster. For example, most projects in cluster 1 are in deep formations, which normally deeper than 3000 ft, and they have medium viscosity, intermediate permeability, high porosity, low to medium temperature, and medium to high oil saturation. In other words, the branch of cluster 1 represents the common reservoir property ranges similarly like the conventional screening methods. However, the other branches also explains different suitable cluster ranges under different reservoir conditions.

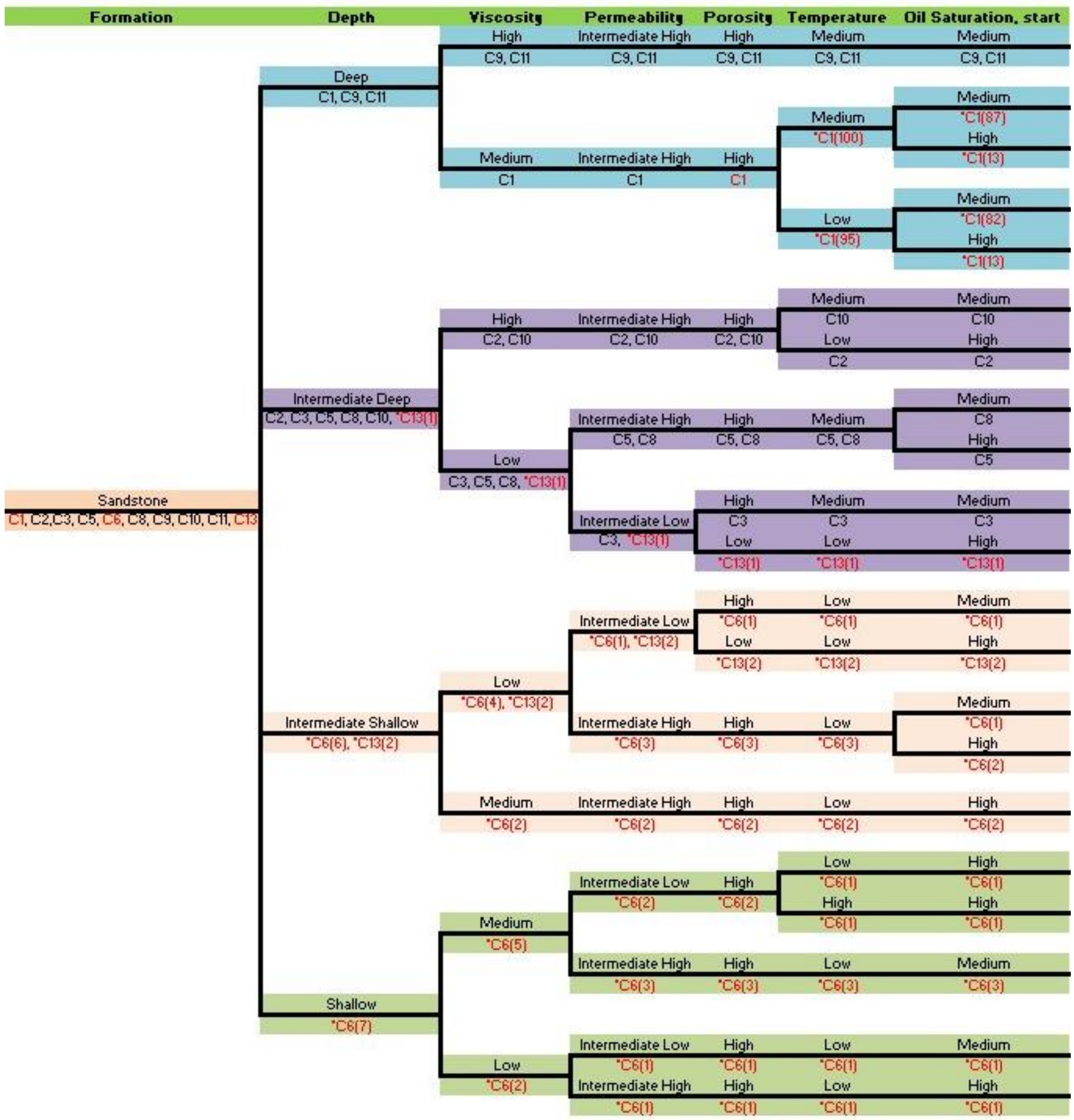


Figure 5.4. Cluster characterization of steam flooding applications on sandstone formations. The red colored clusters have less dominating value ranges so that all the detailed categories are presented; the black colored clusters have dominating categories in respective properties

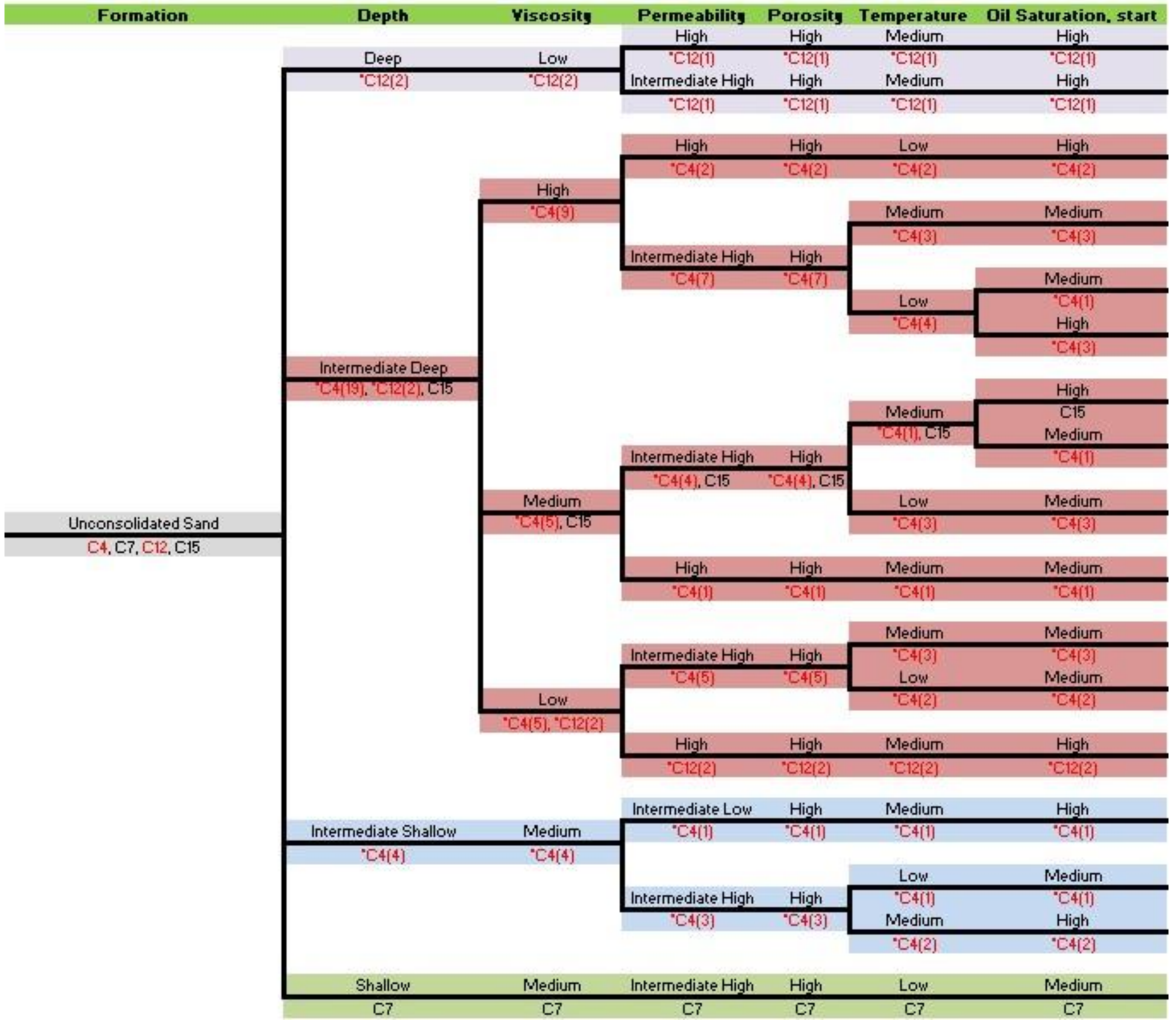


Figure 5.5. Cluster characterization of steam flooding applications on unconsolidated sands formations. The red colored clusters have less dominating value ranges so that all the detailed categories are presented; the black colored clusters have dominating categories in respective properties.

Moreover, steam flooding has a wide application with different reservoir conditions. For sandstone formations, the formation depth varies significantly, from 100 feet to 9000 feet; each depth category reveals different associations among selected properties. For example, deep formation applications correspond to viscous oils, high porosity and intermediate high permeability, initial oil saturation greater than 70%, but there are significant number of applications fall into low temperature range of 45 ~ 100 ˚F; yet shallow formation applications correspond to the same high porosity but lower permeability formations, lower viscous oils and lower formation temperatures.

Comparing with a simple screening table presents in conventional screening methods, by having these two branch charts, more detailed screening information are displayed. Moreover, for a new project, if the formation type is unconsolidated sandstone, and the depth is intermediate deep, the viscosity falls into the range of low, and has high permeability and high porosity, the ranges of temperature and oil saturation could be achieved.

5.2. DESCRIPTIVE STATISTICS

After the clustering results, descriptive statistics methods were utilized to understanding the relationship between reservoir parameters.

5.2.1. Correlation Coefficient. Tables of 5.2 and 5.3 indicate the Pearson's Correlation Coefficient between paired properties for the two biggest clusters (cluster 1 and cluster 2), respectively. From cluster 1, the biggest correlation coefficient is between the viscosity and API, which is -0.33; and the least related features are viscosity and permeability. In cluster 2, the strongest relationship is between API and temperature, which is -0.47, and the least related properties are temperature and permeability.

Table 5.2. Pearson's Correlation Coefficients between paired properties for cluster 1

	Porosity %	***Permeability, md***	***Depth, ft***	***API***	***Viscosity, cp***	***Temperature, F***	***Residual oil Saturation. Start***
Porosity %	1						
Permeability, md	0.06	1					
Depth, ft	-0.30	0.08	1				

Table 5.2. Pearson's Correlation Coefficients between paired properties for cluster 1 (cont.)

API	0.05	0.18	-0.05	1			
Viscosity, cp	-0.20	0.00	0.03	-0.33	1		
Temperature, F	0.07	0.10	0.16	-0.19	-0.27	1	
Residual oil Saturation. Start	-0.07	0.12	-0.08	-0.16	0.14	0.07	1

Table 5.3. Pearson's Correlation Coefficients between paired properties for cluster 2

	Porosity %	***Permeability, md***	***Depth, ft***	***API***	***Viscosity, cp***	***Temperature, F***	***Residual oil Saturation. Start***
Porosity %	1						
Permeability, md	-0.29	1					
Depth, ft	-0.30	0.28	1				
API	-0.09	-0.39	-0.21	1			
Viscosity, cp	0.06	0.20	-0.22	-0.32	1		
Temperature, F	0.31	0.01	0.27	-0.47	-0.11	1	
Residual oil Saturation. Start	-0.06	-0.16	-0.36	-0.16	0.23	-0.21	1

Even though the relationship associations are different in some of the paired properties, for example, in cluster 1, porosity is positively associated with permeability, which is 0.06; while it is negatively associated in cluster 2, which is -0.29, the most of the paired properties have a consistent relationships. For instance, the relationship between API and temperature is always negatively associated, which means with the increase of temperature, the API drops down. Similarly, saturation vs. porosity, depth, and API; API vs. depth, viscosity, and temperature; and temperature vs. viscosity are all negatively correlated. On the other hand, permeability vs. depth and temperature; temperature vs. porosity and depth; and saturation vs. viscosity are positively associated.

5.2.2. Box Plots. To better understanding the characteristics of each clusters, boxplot and bar charts have been used to represents the ranges of each cluster and the distribution of properties for each cluster. These two sets of plots are generated for both sandstone formations and unconsolidated sand formations.

Figures 5.6 to 5.12 present the boxplots of each reservoir parameter, which are porosity, permeability, depth, API gravity, temperature, viscosity and oil saturation at start.

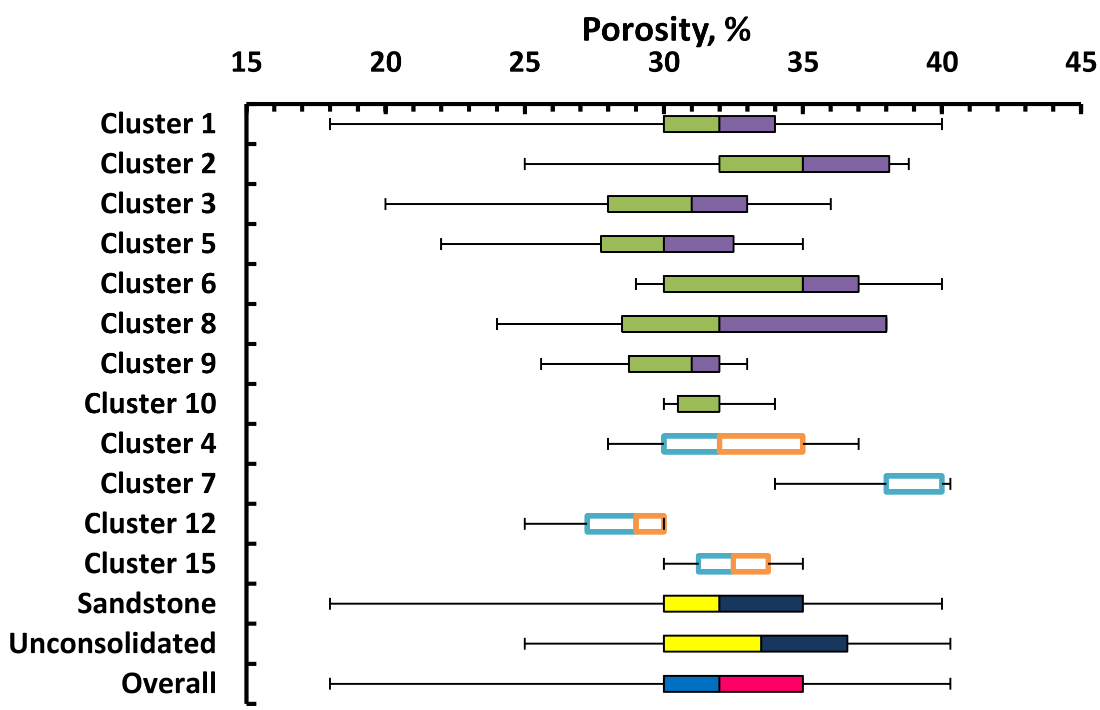


Figure 5.6. Porosity ranges in boxplot for steam flooding projects (from 1980 to 2012 Oil and Gas Journal)

From this plot, the overall ranges of porosity for steam flooding projects is from 18 to 40.5. The difference between sandstone formation and unconsolidated sandstone formation is not obvious. However, unconsolidated sandstone formation tends to have relatively biased porosity. For example, cluster 7 mainly includes the steam flooding projects with high porosity, while main projects in cluster 12 has low porosity. For both formation type, most projects falls into the porosity ranges from 30 to 35.

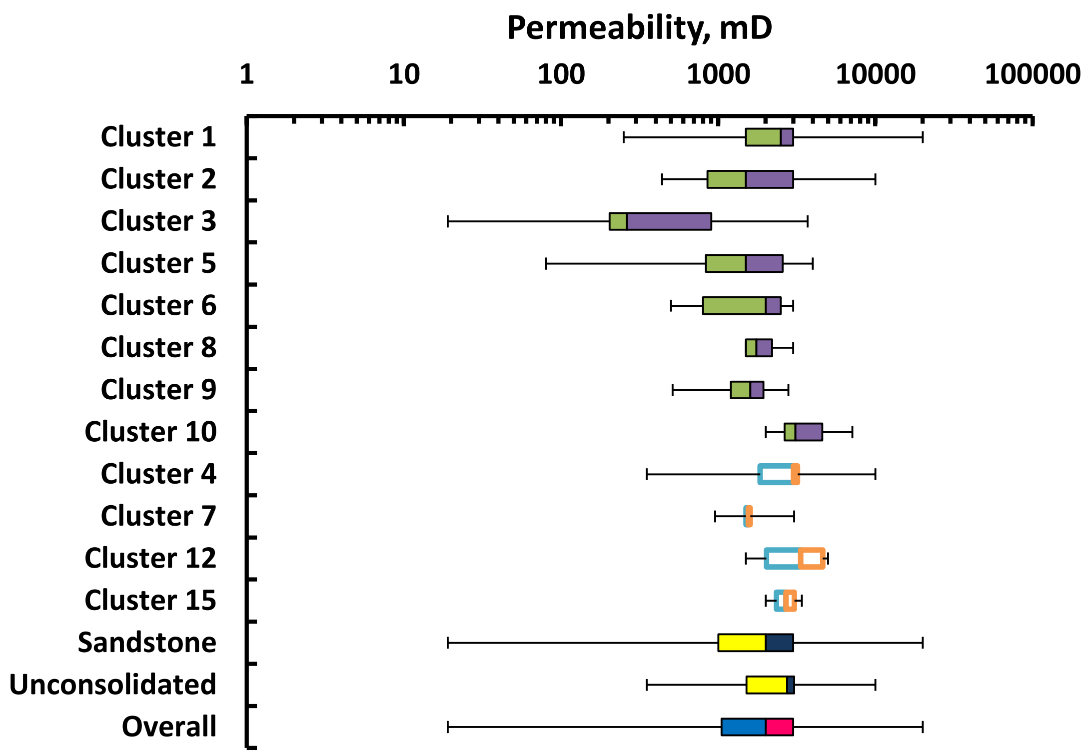


Figure 5.7. Permeability ranges in boxplot steam flooding projects (from 1980 to 2012 Oil and Gas Journal)

Figure 5.7 above presents the ranges of permeability for steam flooding projects. The overall ranges of permeability is from 11mD to about 20000 mD, and most of the projects have the permeability from 1000 mD to 3000 mD. For the sandstone formation type, the permeability of cluster 3 seems to have large distance with other clusters because this cluster involves the majority of the projects with low permeability. Cluster 10 tends to include the projects with high permeability. For the unconsolidated formation type, the ranges of permeability is relatively more concentrated because there are less steam flooding projects with this formation type compared with sandstone formations. As we could see in the plot, most projects in cluster 7 has almost the same permeability values, which is about 1500 mD.

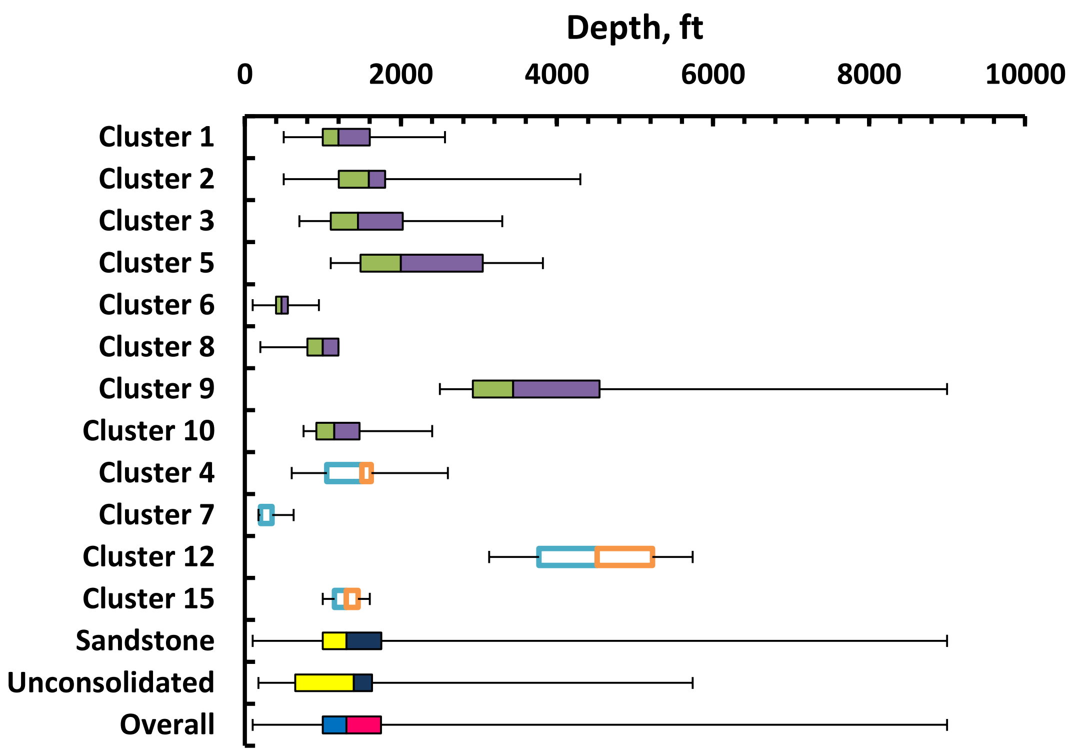


Figure 5.8. Depth ranges in boxplot steam flooding projects (from 1980 to 2012 Oil and Gas Journal)

Figure 5.8 shows the ranges of depth for steam flooding projects. The overall projects have a huge ranges from extremely shallow reservoirs (about 100 ft) to very deep reservoirs (about 9200 ft). Based on the ranges of each cluster, we could find that some of the clusters are very unique, and some of the clusters have similar ranges. For example, cluster 6 and cluster 7 are very special in terms of depth among all clusters, both of them includes the projects with extremely shallow reservoirs. Cluster 1, 2, and cluster 3 have similar ranges of depth, which means the distance of depths for these three clusters are very small.

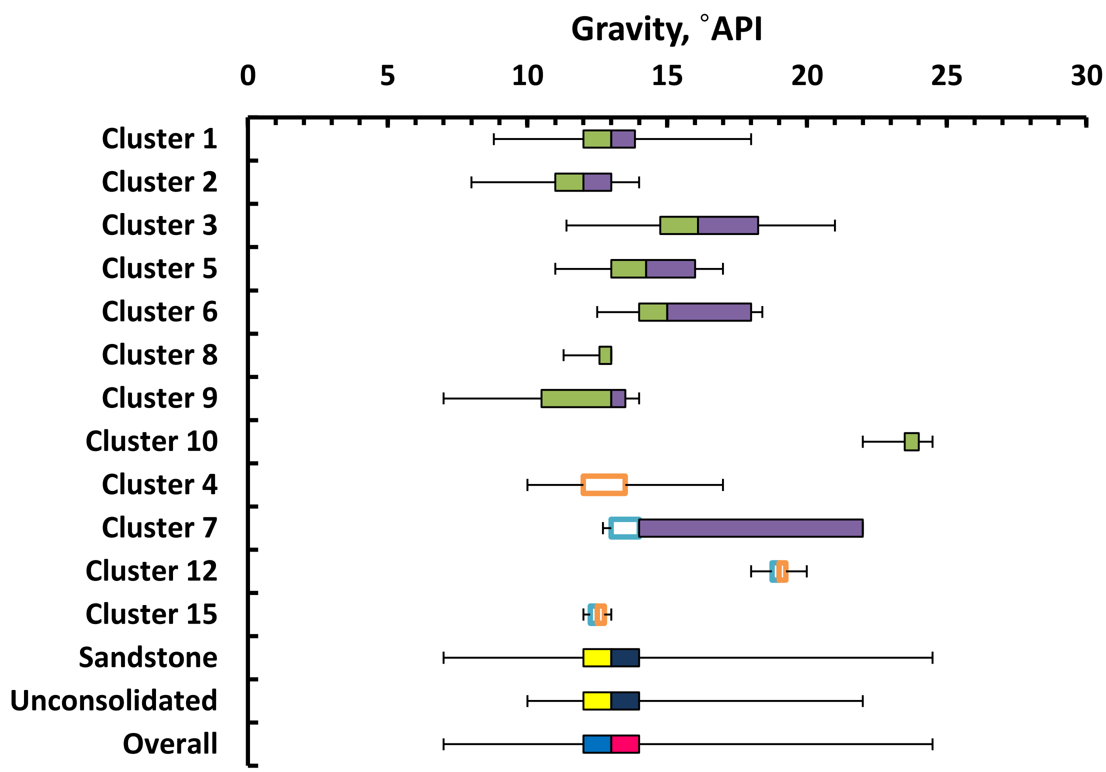


Figure 5.9. Gravity ranges in boxplot for steam flooding projects (from 1980 to 2012 Oil and Gas Journal)

Figure 5.9 illustrates the ranges of API gravity for all clusters, which is from 7 ˚API to 25 ˚API. This ranges indicates that all the steam flooding projects in this data set are heavy oil. What’s more, it is very surprising that the main ranges of gravity for both sandstone formation type and unconsolidated formation type are exactly the same, which shows that the formation type does not have large influence to the oil gravity.

By combing all the above plots together, these boxplots indicate that several clusters have their own special and concentrated small ranges of gravity, like cluster 8, cluster 10, cluster 12, and cluster 15. In contrast with the small ranges of permeability, porosity, and depth, cluster 7 has a very large ranges of API gravity, which indicates that the gravity in cluster 7 is very different, and this might be the reason why cluster 7 did not merge with other clusters. Moreover, cluster 10 is very special with the parameter of gravity as well, which has the highest gravity among all clusters.

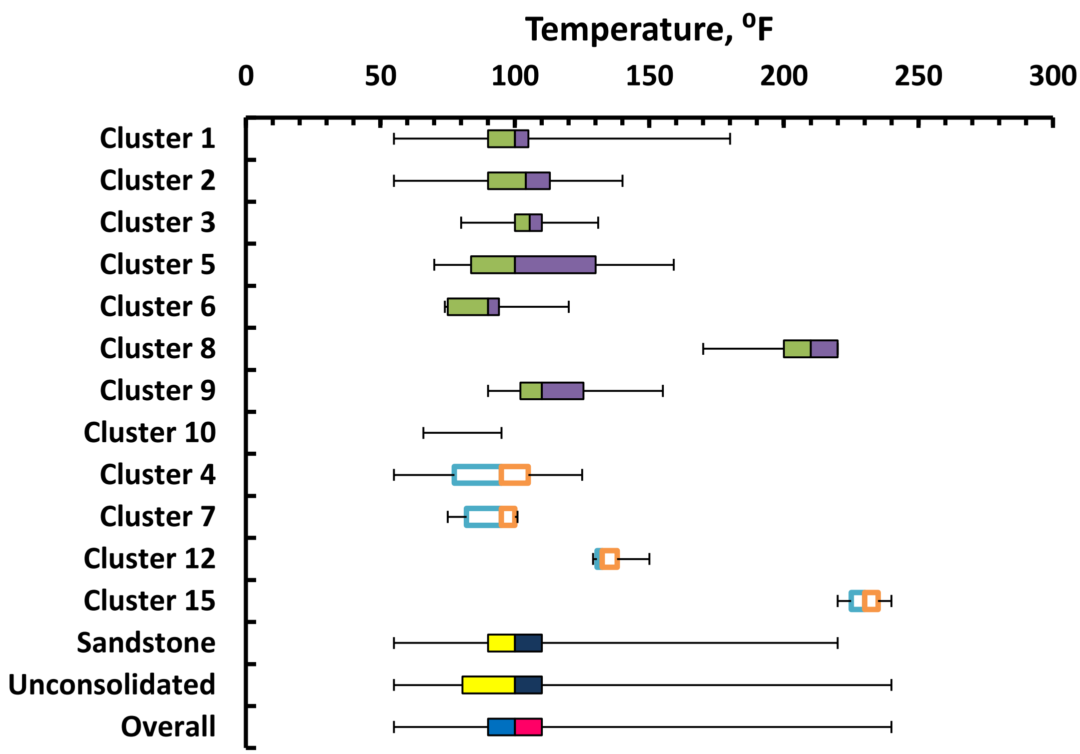


Figure 5.10. Temperature ranges in boxplot for steam flooding projects (from 1980 to 2012 Oil and Gas Journal)

Figure 5.10 illustrates the ranges of temperature, which is from 55 ˚F to about 235 ˚F. Surprisingly, even though there are way less steam flooding projects with unconsolidated sandstone formation, the ranges of temperature is bigger than the temperature for the projects with sandstone formation, which may indicate that the formation type might be a factor that affect reservoir temperature. In addition, the boxplot of cluster 10 is just a line, which shows that the temperature in this cluster just have 2 different values. When check back the temperature in the cluster 10, 6 projects coincidentally have exactly same value of temperature (66 ˚F) even though they have totally different values for other reservoir parameters. Therefore, temperature might be a dominating feature for cluster 10.

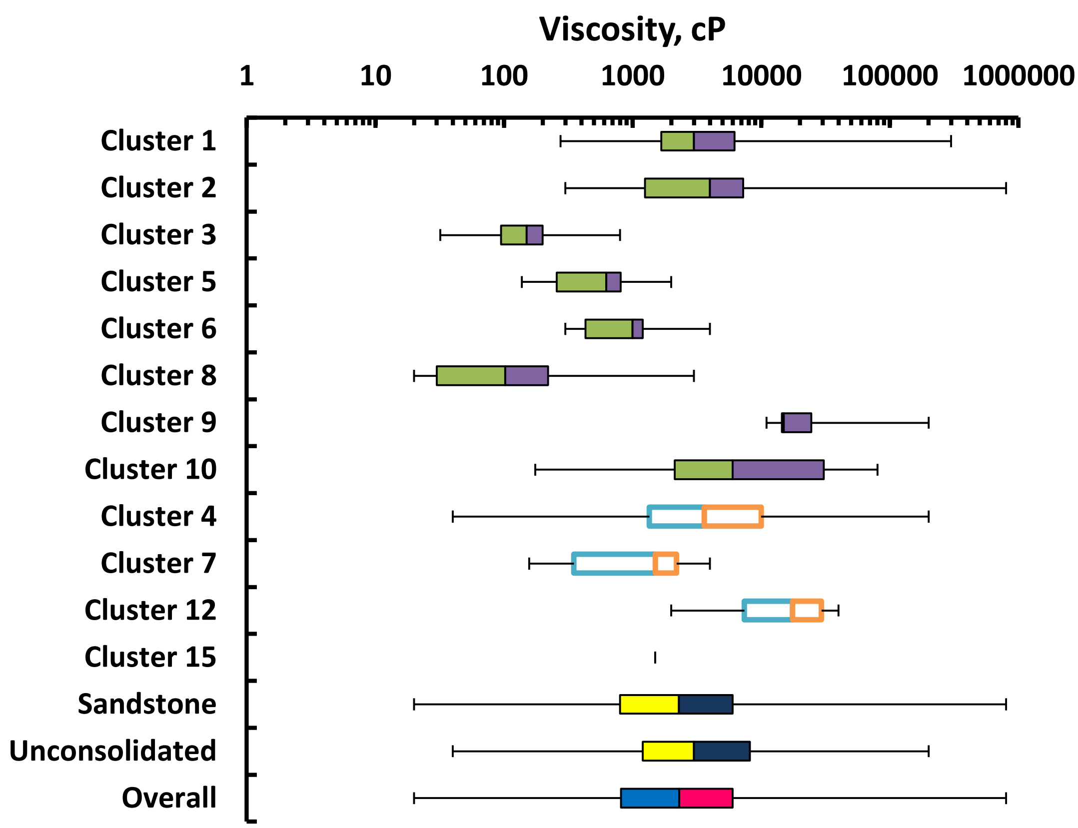


Figure 5.11. Viscosity ranges in boxplot for steam flooding projects (from 1980 to 2012 Oil and Gas Journal)

Figure 5.11 presents the ranges of viscosity for each cluster. The overall ranges of viscosity is very huge, from 11cP to 1000000 cP, and most projects falls into the range from 700 cP to 5000 cP. Cluster 15 in the plot is presented by a single line, which means all the steam flooding projects in cluster 15 have the same value of viscosity, which is 1500 cP. From the plot, cluster 1 and cluster 2 tends to involve the projects with high viscous fluids, while cluster 3 and cluster 8 tends to have the low viscous fluids.

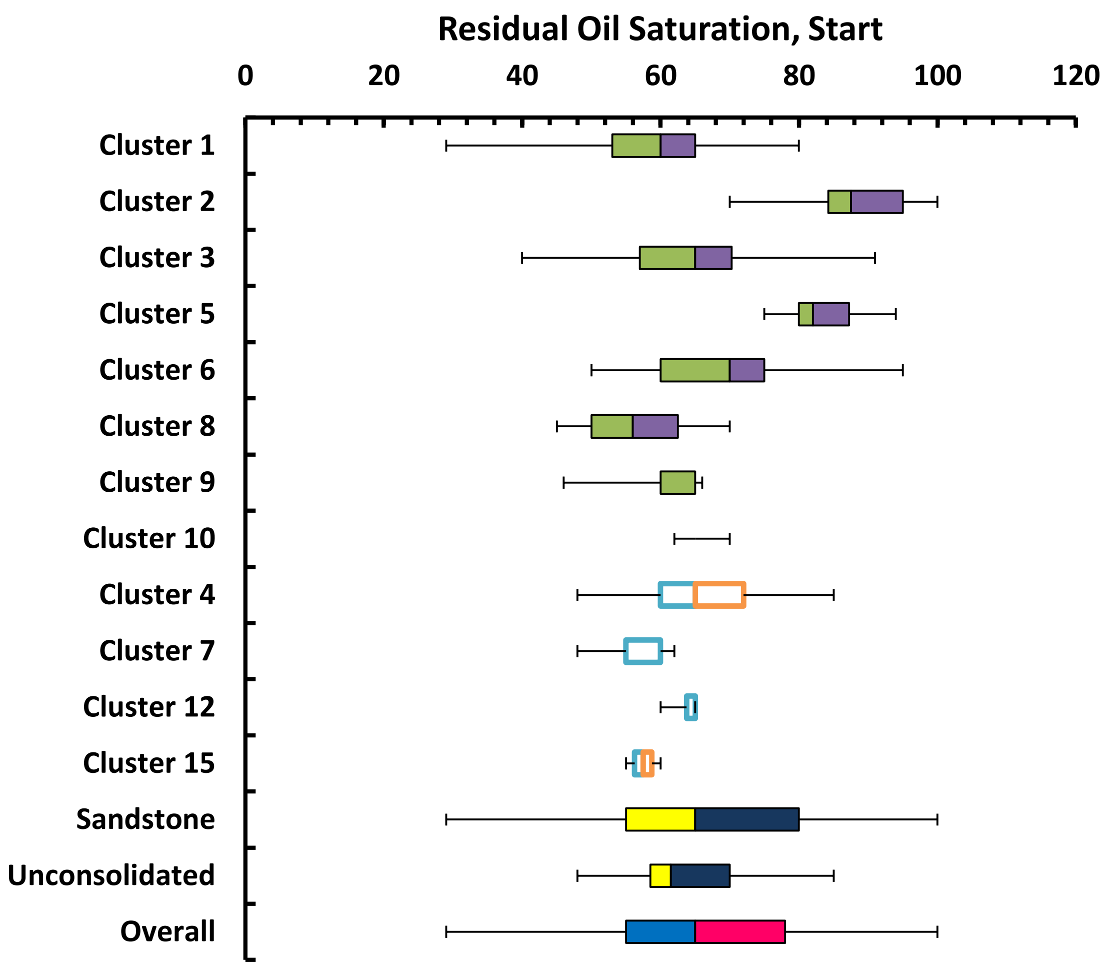


Figure 5.12. Residual oil saturation ranges in boxplot for steam flooding projects (from 1980 to 2012 Oil and Gas Journal)

Figure 5.12 indicates the oil saturation ranges before the implementation of steam flooding. The overall ranges of oil saturation is from 29 to 100. As shown in this plot, the main ranges to each cluster is very distinctive. For example, cluster 1 has the main ranges from 53 to 65; cluster 2 has the main ranges from 84.25 to 95. Also, the saturation of cluster 12 is from 63.75 to 65, and the saturation range for cluster 15 is from 56.25 to 58.75.

5.2.3. Bar Charts. From Figure 5.13 to Figure 5.18, the bar charts are used to indicate the number of record and distributions for each specific ranges of reservoir properties.

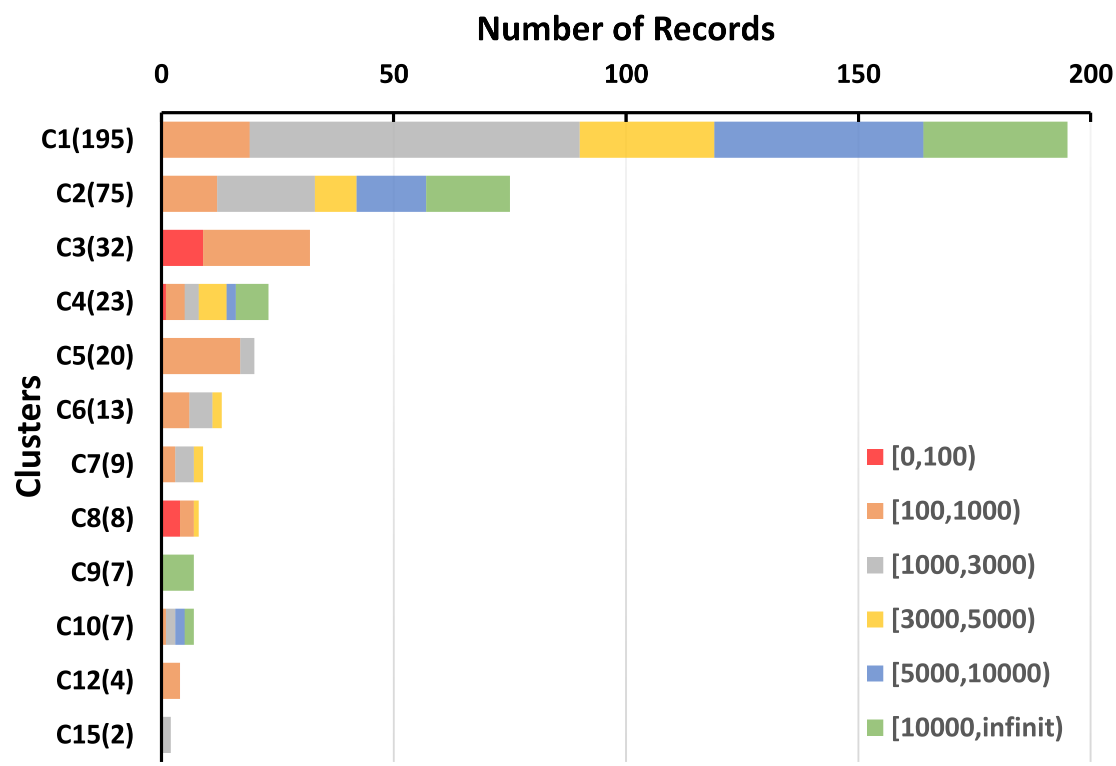


Figure 5.13. Viscosity project records distributions for steam flooding projects (from 1980 to 2012 Oil and Gas Journal)

As shown in Figure 5.13 above, the main viscosity ranges of cluster 1 and cluster 2 is from 1000 cP to 3000 cP. The main ranges of cluster 3 and cluster 5 is from 100cP to 1000 cP, and cluster 3 also includes the majority projects with the low viscosity. Moreover, all the projects in cluster 9 have really high viscosity, and the rest clusters have relatively medium ranges of viscosity, which is not too low nor not too high.

Figure 5.14 indicates the clear distributions of porosity to each cluster. At the first glance, we could see that about 80% to 90% of the whole steam flooding projects have the range of porosity from 30 to 40. Only cluster 1, cluster 6, and cluster 7 include the high porosity, which is from the range of 40 to 50. This bar chart also illustrate that only cluster 1 includes the steam flooding projects with low porosity.

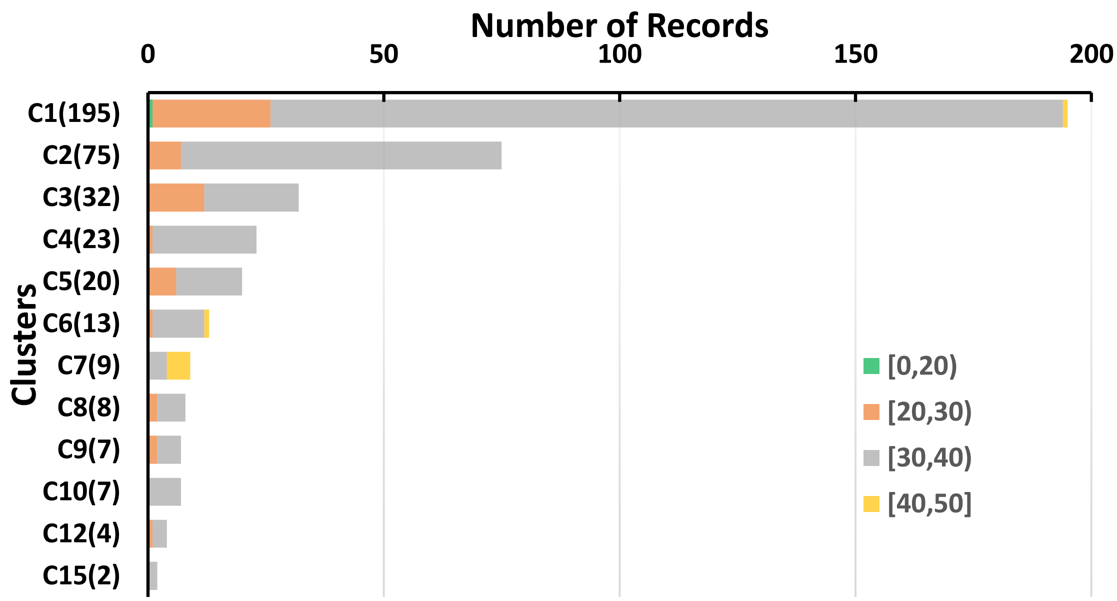


Figure 5.14. Porosity project records distributions for steam flooding projects (from 1980 to 2012 Oil and Gas Journal)

Figure 5.15 shows the range records of depth to each cluster. The dominating ranges for cluster 1 is from 1000 ft to 1500 ft. For cluster 6, cluster 7, and cluster 8, they includes the projects locates at the extremely shallow areas. What's more, this plot indicates that only cluster 9 have the projects with very deep reservoirs.

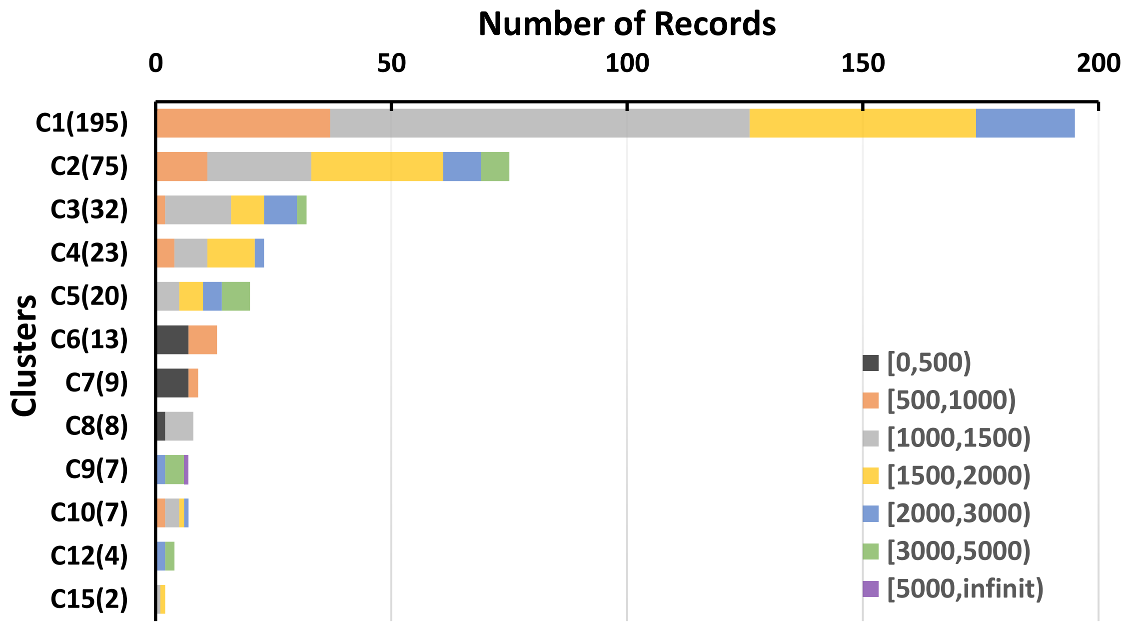


Figure 5.15. Depth project records distributions for steam flooding projects (from 1980 to 2012 Oil and Gas Journal)

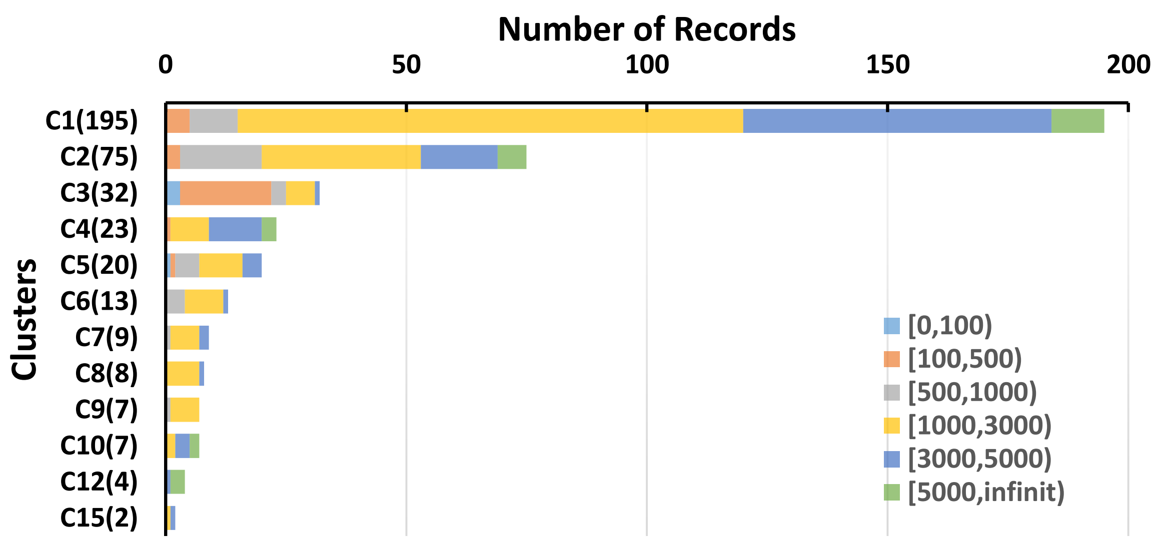


Figure 5.16. Permeability project distributions for steam flooding projects (from 1980 to 2012 Oil and Gas Journal)

Figure 5.16 shows the records of permeability for different ranges. As we could see, almost all the clusters have the permeability ranges from 1000 mD to 3000 mD, except cluster 12. This range also occupies most of the records in cluster 1, and involved the highest records in cluster 2, 5, 6, 7, 8, and cluster 9 as well. There are several clusters includes the projects with high permeability, which are cluster 1, 2, 4, 10, and cluster 12.

Figure 5.17 presents the range records of temperature for each cluster. From the plot, we could see that most clusters have the most records from either 80 ˚F to 100 ˚F, or from 100 ˚F to 120 ˚F. Cluster 8 and cluster 15 seem to be a little bit different which they only have the records of extremely high reservoir temperatures, from 180 ˚F to 240 ˚F. Moreover, cluster 1, 2, and 4 include the all the projects with low temperature, which is just from 45 ˚F to 60 ˚F.

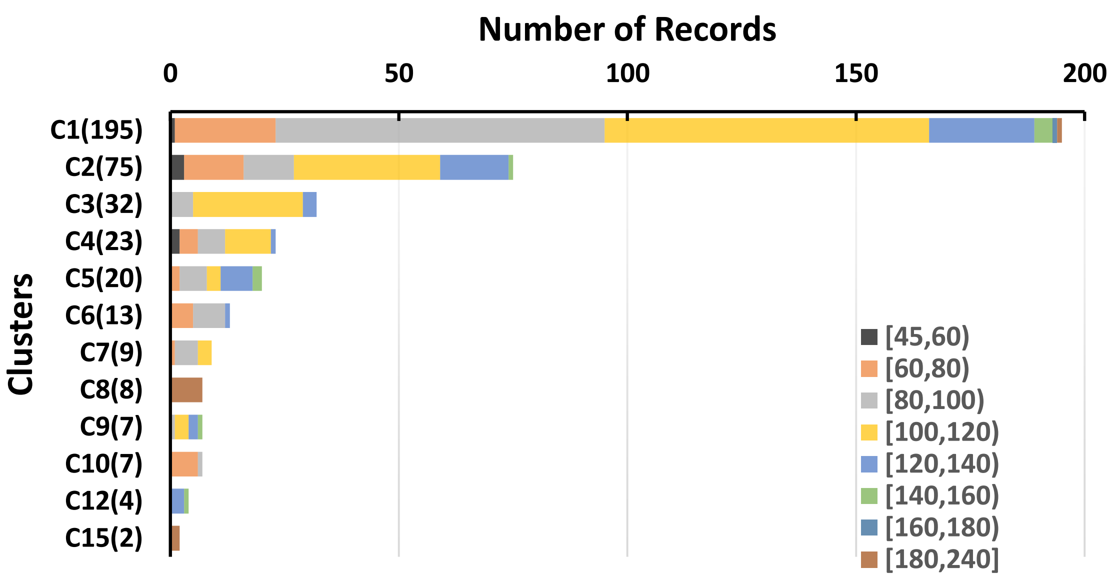


Figure 5.17. Temperature project records distributions for steam flooding projects (from 1980 to 2012 Oil and Gas Journal)

Figure 5.18 illustrates the record ranges of oil saturation before the implementation of steam flooding techniques. Before using steam flooding, we could see that most clusters already have relatively high oil saturation. For example, the biggest number of records in cluster 1 has the saturation from 60 to 70 already, which is pretty high. For cluster 2, most of the projects even have the oil saturation from 80 to 100. Only cluster 1 has the projects with low oil saturation.

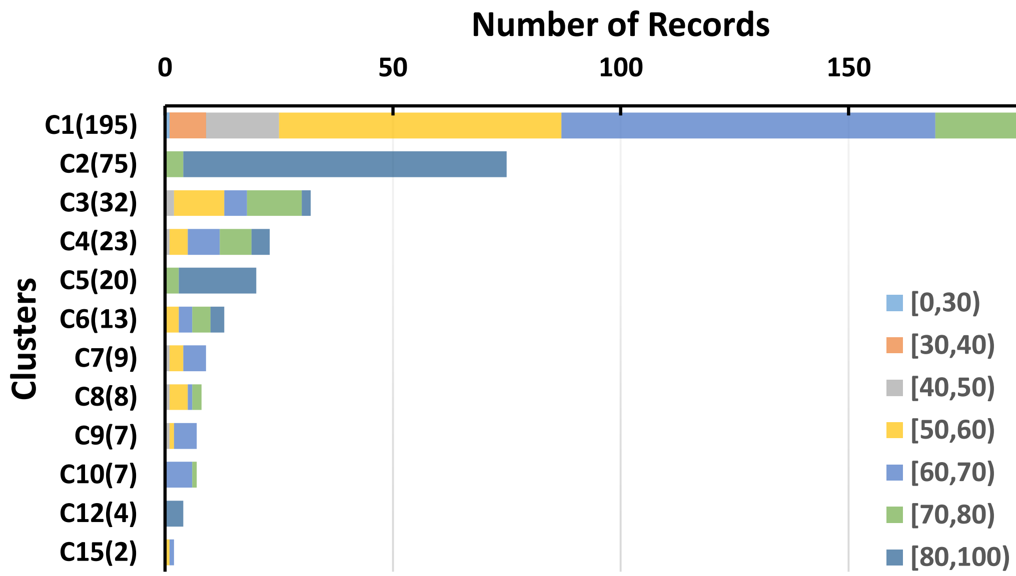


Figure 5.18. Oil saturation project records distributions for steam flooding projects (from 1980 to 2012 Oil and Gas Journal)

Therefore, each clusters of steam flooding projects could be effectively and clearly characterized by using hierarchical clustering algorithm. However, several steps still need to take to get better results:

1. Change the range of each properties, so a smaller range of each cluster could be achieved.

2. Use other clustering algorithm to process this data set to study which algorithm works best for steam flooding projects.

5.2.4. Descriptive Statistics Summaries. In order to draw the rules for each cluster, and to better characterize the clusters for each data set, the descriptive statistics have been summarized. For steam flooding projects, four new clusters were formed based on the existing 20 clusters and the dendrogram, as shown in Table 5.4.

Table 5.4. 20 clusters merged into 4 big clusters for steam flooding projects

New Cluster	**Merged Clusters**
Cluster 1	Clusters 1, 2, 6, 9, 10, 11
Cluster 2	Clusters 3, 5, 8, 13
Cluster 3	Clusters 4, 7, 12, 15, 16, 17, 20
Cluster 4	Clusters 14, 18, 19

Figure 5.19 indicates the descriptive statistic summaries for steam flooding clusters. As shown in the figure, the porosity does not distinct with each other between clusters, except cluster 4 concludes the steam flooding projects with relatively low porosity (18%). What's more, cluster 1 and cluster 3 involve the projects with high permeability and high viscosity; cluster 2 and cluster 4 have the projects with extremely high temperature; and cluster 3 includes the projects with rarely deep formations (9000 ft).

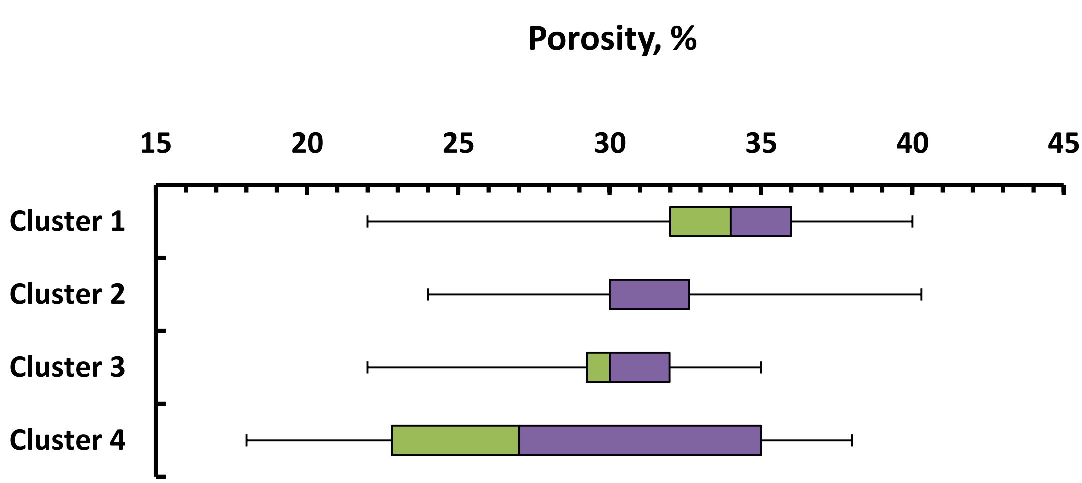


Figure 5.19. Properties summaries for steam flooding (from 1980 to 2012 Oil and Gas Journal)

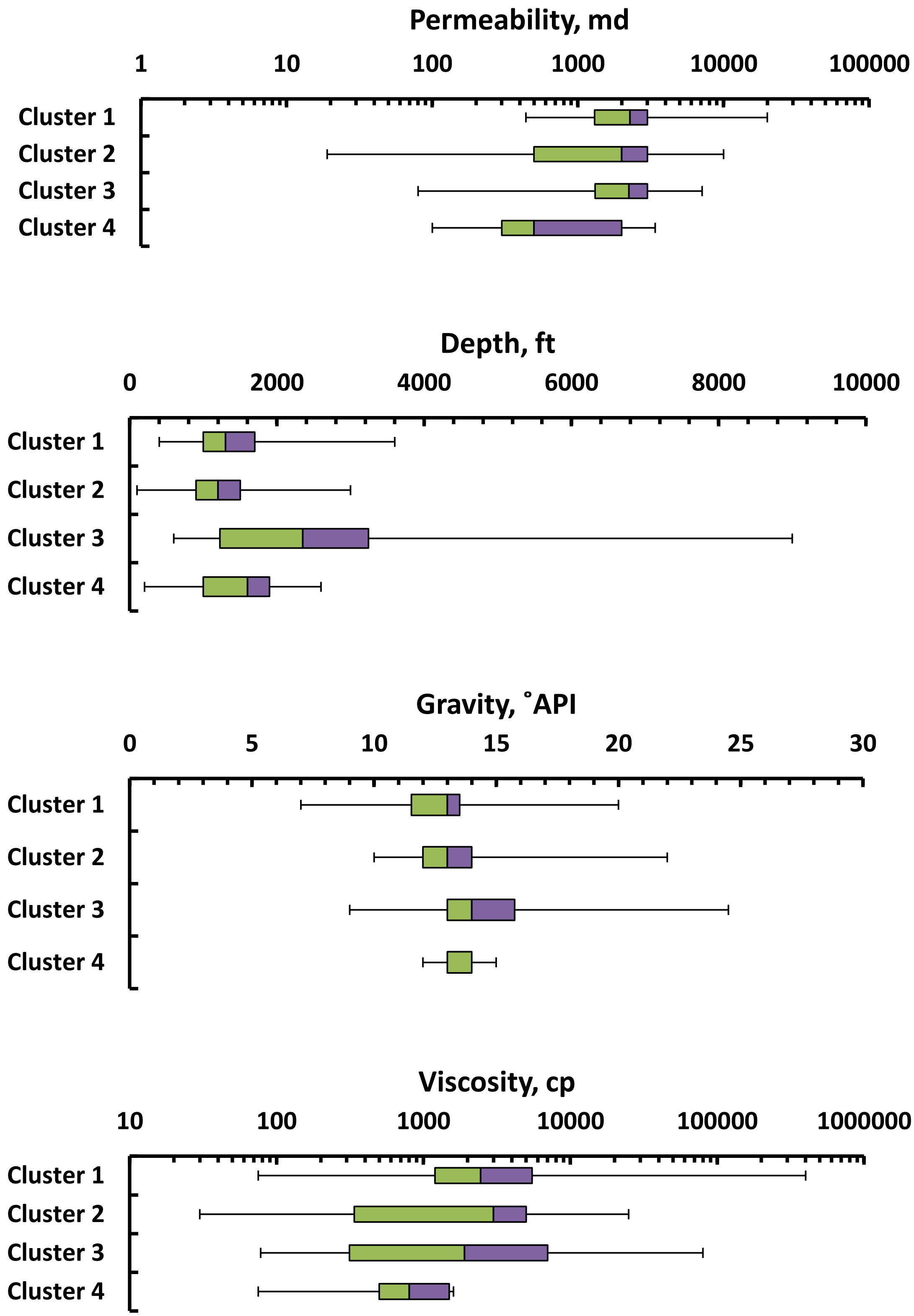
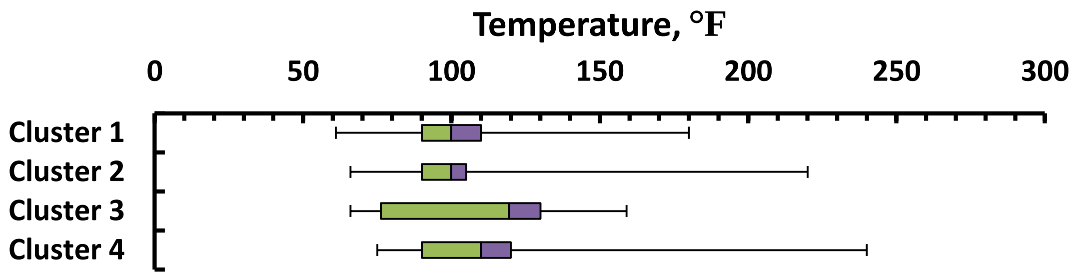


Figure 5.19. Properties summaries for steam flooding (from 1980 to 2012 Oil and Gas Journal) (cont.)



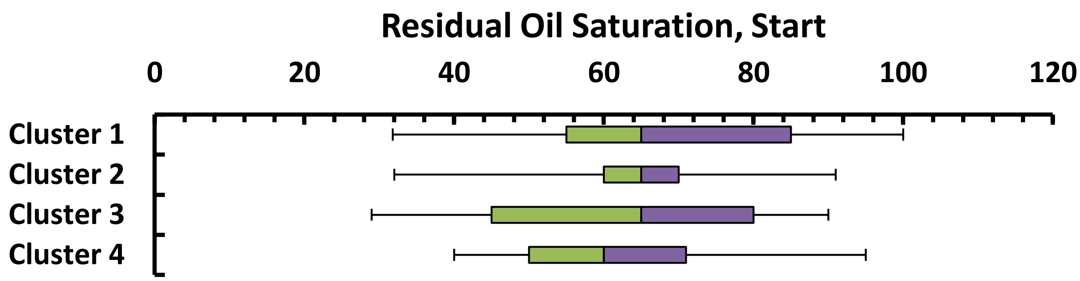


Figure 5.19. Properties summaries for steam flooding (from 1980 to 2012 Oil and Gas Journal) (cont.)

5.3. PRINCIPAL COMPONENT ANALYSIS

Figure 5.20 is a mono plot for steam flooding projects. the length of the viscosity vector is the largest, and is closest to the circle, this results represents that viscosity is the most important reservoir parameters in the steam flooding projects. Moreover, depth and permeability are also long vectors in the mono plot, therefore, these two reservoir parameters are also very important in the steam flooding projects compared with other parameters (temperature, oil saturation, gravity, and porosity). On the other hand, the mono plot also illustrates that permeability and depth are almost not correlated, and viscosity is negatively correlated with permeability and depth, respectively.

By comparing the results from the study of correlation coefficient and the mono plot, the mono plot is a better way to figure out the relationships among reservoir properties, and also a better methods to find the dominating features in the data sets. Therefore, correlation coefficient is not used for the worldwide EOR projects.

The clustering results in a scatter plot is shown in Figure 5.21. As indicated in the figure, the first components retained 61% of the variations, and the second component retained 32% of variations. Therefore, visualize the clustering result in two dimensions is good enough because this 2D plot indicates 93% variance of the steam flooding projects.

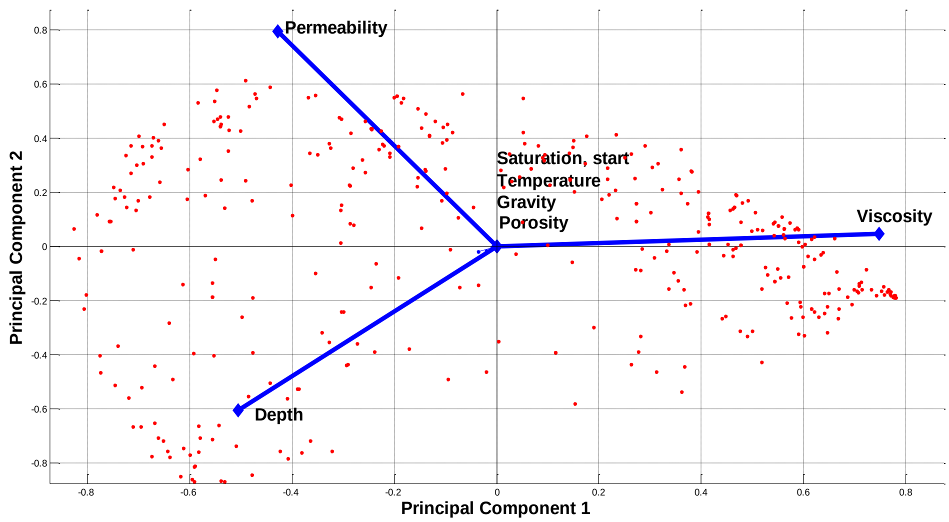


Figure 5.20. Mono plot for steam flooding projects (from 1980 to 2012 Oil and Gas Journal)

However, the active boundaries for each cluster is not clear. Figure 5.22 to 5.25 present the detailed cluster distributions for each formed cluster. For each cluster, it is obvious that projects belong to the same cluster are tending to group together. For example, the yellow cluster in cluster 1 has clear boundary in the scatter plot; the green and pink clusters are very distinctive in cluster 2; black and pink clusters in clusters are also obvious; and in cluster 4, the pink cluster has clear boundary.

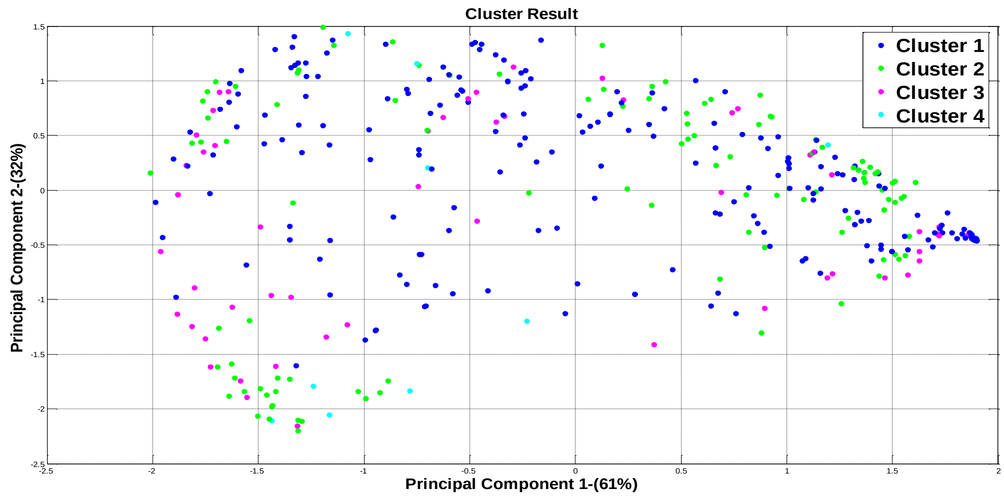


Figure 5.21. Steam flooding projects with all clustering results (from 1980 to 2012 Oil and Gas Journal)

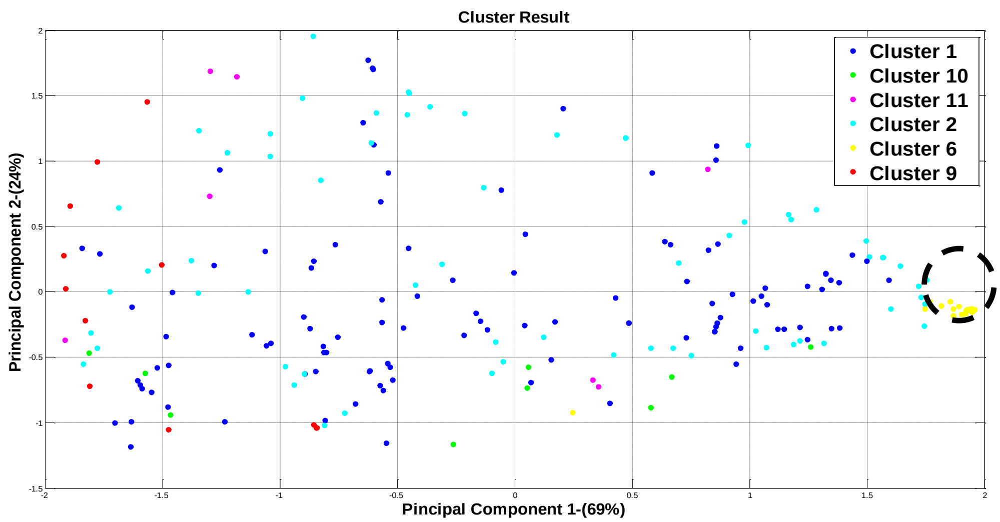


Figure 5.22. Detailed clustering distributions for cluster 1

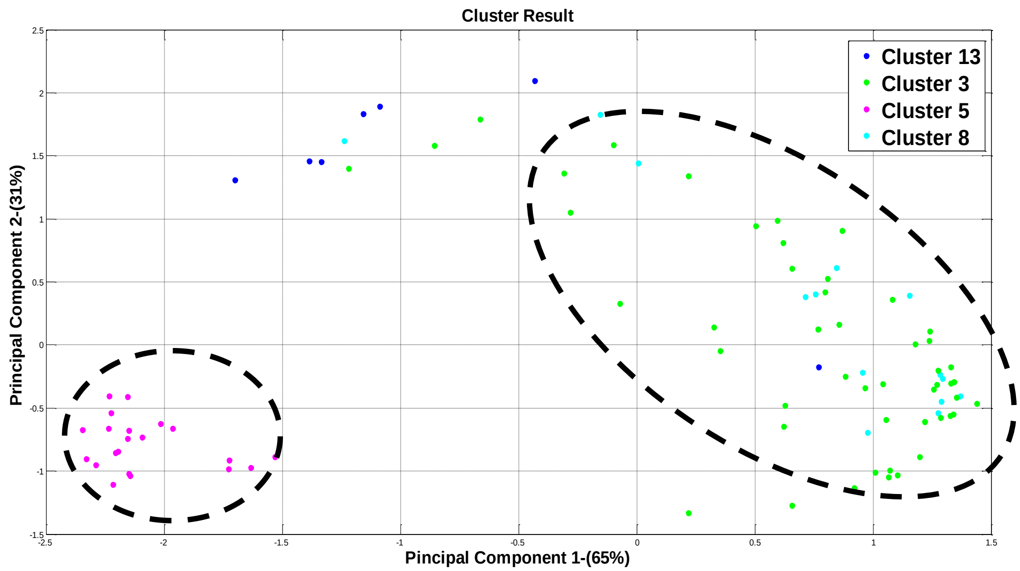


Figure 5.23. Detailed clustering distributions for cluster 2

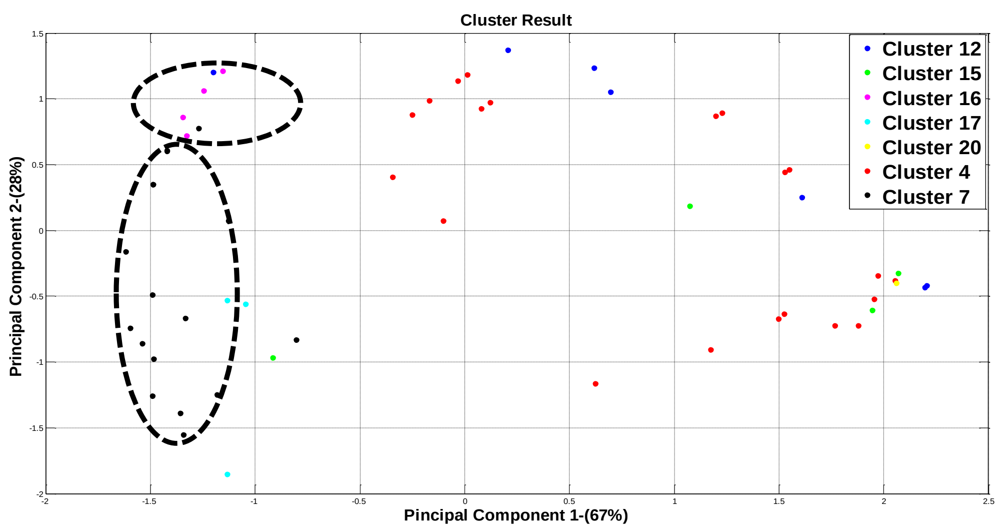


Figure 5.24. Detailed clustering distributions for cluster 3

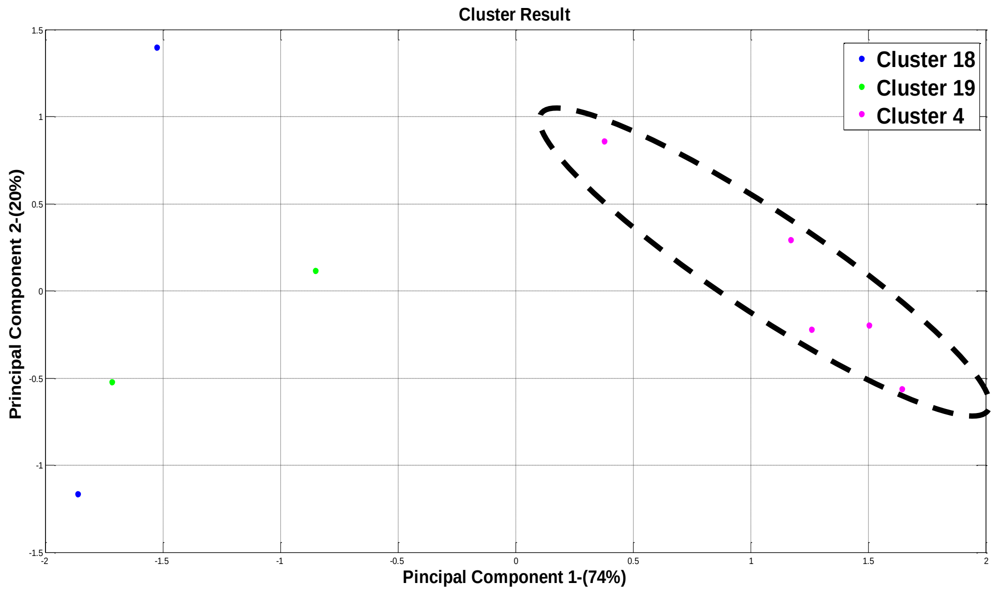


Figure 5.25. Detailed clustering distributions for cluster 4

Therefore, by having the scatter plots, the location relationships among clusters are clearly laid out, which helps to visualize the cluster results in a 2D view.

6. RESULTS FROM THE WORDWIDE EOR DATA SETS

6.1. HIERARCHICAL CLUSTERING RESULTS

Same with the procedures conducted for the steam flooding projects, after the implementation of hierarchical clustering algorithm to the worldwide EOR projects, 20 clusters were received. The dendrogram from the program is shown in Figure 6.1 below, and the detailed dendrogram based on EOR methods is illustrated in Figure 6.2.

As indicated in Figure 6.2, the hierarchy structure of all the EOR projects are quite clear based on the EOR methods. Table 6.1 illustrates the abbreviations in this dendrogram. Similar with the steam flooding dendrogram, each element in the dendrogram represents the hierarchical clustering result at each clustering level. Taking cluster 2 in the cluster level of 7 as an example, C2 (213ST+7HW+3CB+2PO) indicates that this cluster is made up of 213 steam flooding projects, 7 projects by using hot water, 2 projects with combustion, and 2 projects with polymer flooding.

In addition, from this dendrogram, cluster 10 with 18 steam projects and cluster 20 with 1 steam flooding project are considered as outliers or special cases because these clusters are very stable from the beginning of the dendrogram till almost the end of the dendrogram. Two main EOR techniques are distinguished each other on the dendrogram. The left side represents the projects with steam flooding projects, and the CO_2 miscible flooding projects are illustrated on the right.

For the CO_2 miscible flooding projects, cluster 4 which has 43 CO_2 miscible projects is considered as special cases based on the analysis of the dendrogram. Therefore, from these two dendrograms, first, the outliers and special cases were easily detected; second, the dendrogram is clearly laid out based on different EOR techniques, which means even though the decision attribute was not clarified, the hierarchical clustering algorithm is able to detect the importance of each input attribute based on the analysis.

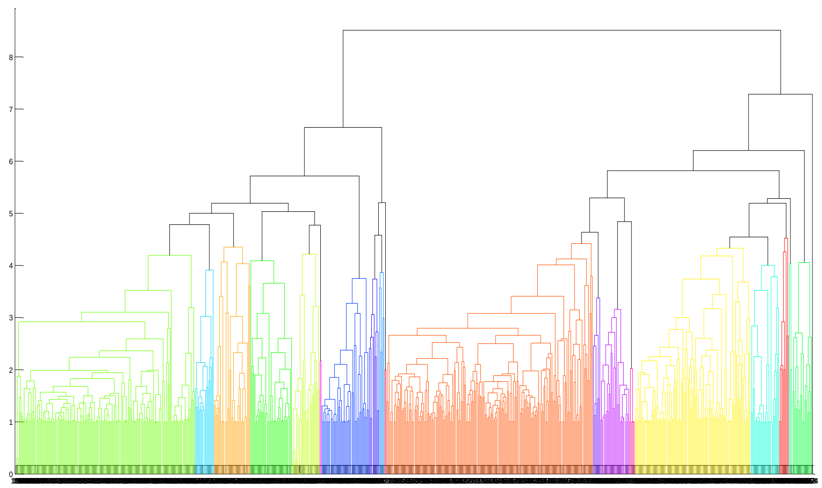


Figure 6.1. Worldwide EOR projects clustering results (from 1996 to 2012 Oil and Gas Journal)

Table 6.1. Dendrogram abbreviations for worldwide EOR projects

Abbreviations	Represents
ST	Steam
CB	Combustion
HW	Hot Water
CM	CO2 Miscible
HM	Hydrocarbon Miscible
HI	Hydrocarbon Immiscible
NI	Nitrogen Immiscible
NM	Nitrogen Miscible
MB	Microbial
CI	CO2 Immiscible
PO	Polymer
CH	Chemical
SU	Surfactant

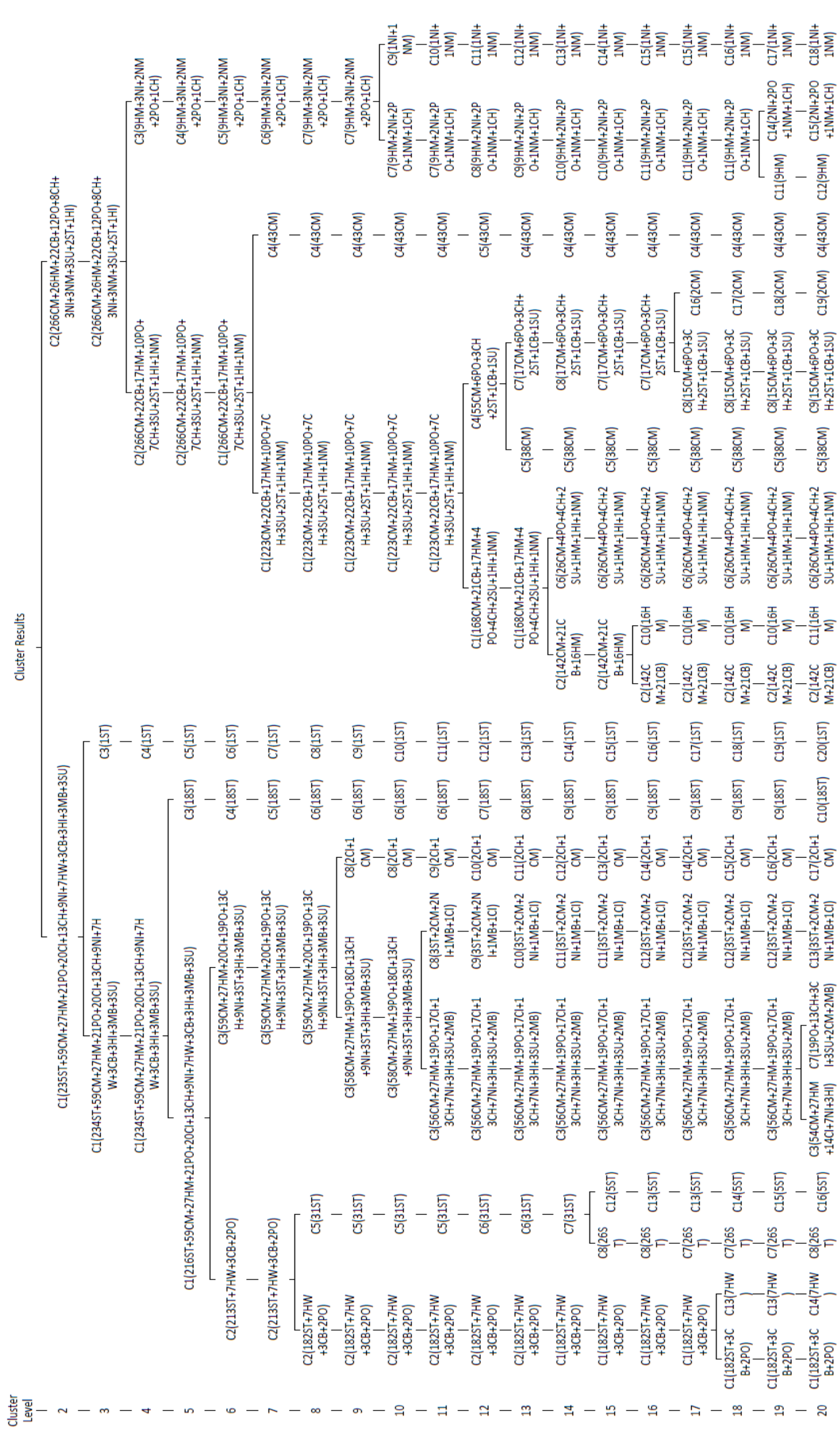


Figure 6.2. Hierarchical clustering results based on EOR methods at clustering level 20 (from 1996 to 2012 Oil and Gas Journal)

Since it is useless to come up with the whole ranges of EOR projects, branch charts are not generated for the clustering results analysis; however, we will do validation and prediction for the worldwide EOR projects to fulfill our objectives for this research.

6.2. DESCRIPTIVE STATISTICS

6.2.1. Box Plots. Even though we got 20 clusters from the hierarchical clustering results, from Figure 6.2, we could find that the clustering result is more stable at cluster level 7. Therefore, we formed 6 main clusters at this level to analyze the clustering results and also to visualize our data. The merged clusters are indicated in Table 6.2 below.

Table 6.2. 20 clusters merged into 6 big clusters for whole EOR projects

New Cluster	**Merged Clusters**
Cluster 1	Clusters 1, 8, 14, 16
Cluster 2	Clusters 3, 7, 13, 17
Cluster 3	Clusters 10, 20
Cluster 4	Clusters 2, 5, 6, 9, 11, 19
Cluster 5	Cluster 4
Cluster 6	Cluster 12, 15, 18

Figures 6.3 to 6.10 present the box plots of each reservoir parameter for the worldwide EOR projects, which are porosity, permeability, depth, API gravity, temperature, viscosity, oil saturation at start, and oil saturation at end.

Figure 6.3 indicates the ranges of porosity for the whole EOR projects. As we could see clearly that the overall porosity ranges is very huge, from about 5 to 75. For cluster 4 and cluster 6, they include the EOR projects with low porosity, while, on the other hand, cluster 3 have all the projects with extremely high porosity, and the major porosity range for cluster 3 is from 60 to 65, which is way higher than the normal porosity values. Therefore, cluster 3 is a special cluster in terms of porosity among all clusters.

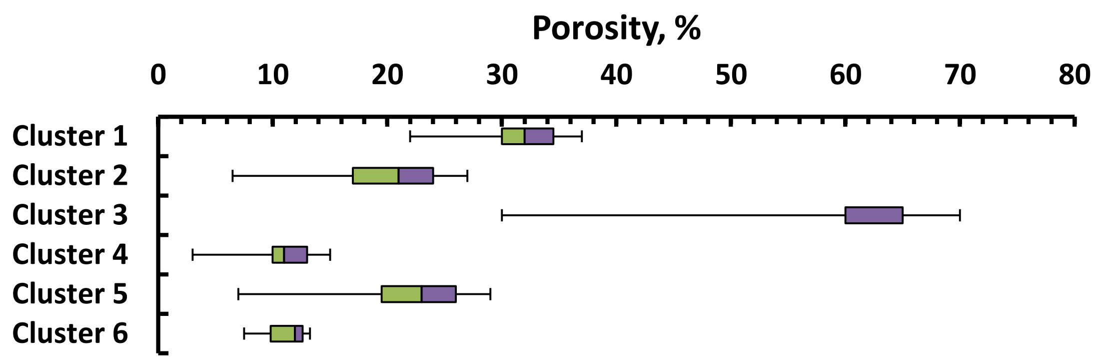


Figure 6.3. Porosity ranges in boxplot for whole EOR projects (from 1996 to 2012 Oil and Gas Journal)

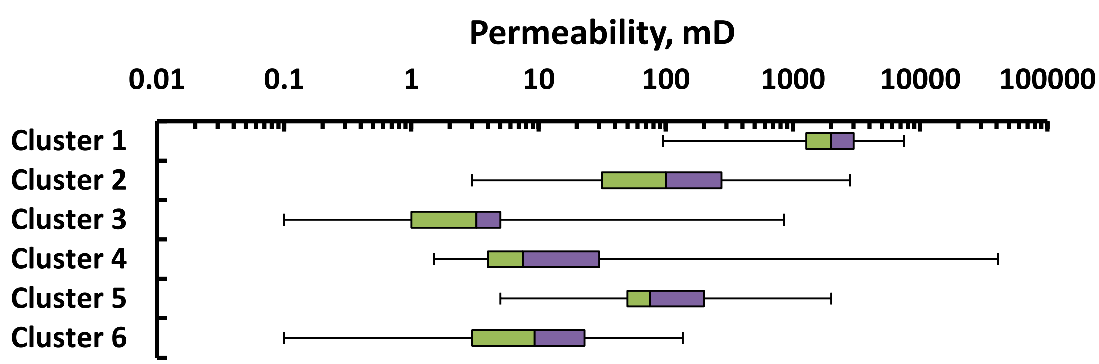


Figure 6.4. Permeability ranges in boxplot for whole EOR projects (from 1996 to 2012 Oil and Gas Journal)

Figure 6.4 shows the ranges of permeability among all clusters. The ranges of permeability is very large, from 0.1 mD to 50000 mD. By comparing the main part of the boxplot, cluster 1 has the highest ranges of permeability while cluster 3 has the lowest ranges of permeability. What's more, cluster 3 and cluster 6 include the lowest permeability among all clusters, while cluster 4 have the projects with extremely high value of permeability.

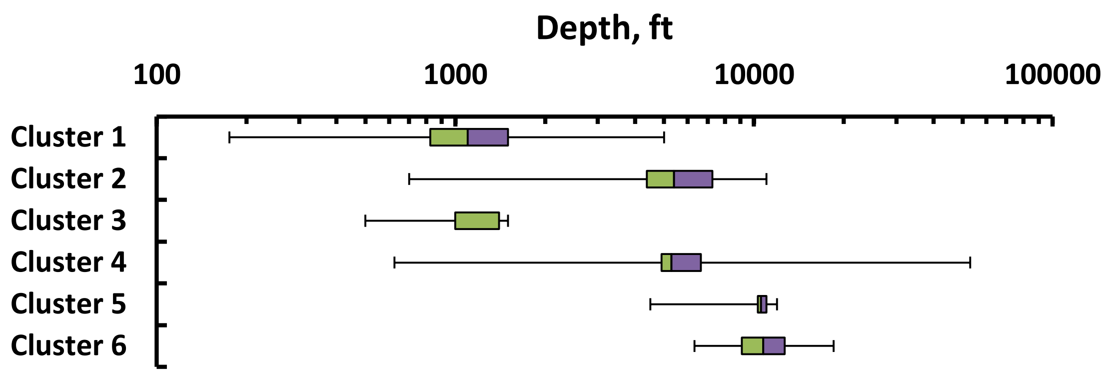


Figure 6.5. Depth ranges in boxplot for whole EOR projects (from 1996 to 2012 Oil and Gas Journal)

Figure 6.5 depicts the ranges of depth of each cluster. There are mainly two categories among these depth ranges. One is with the depth around 1000 ft, which is in the shallow reservoir, as illustrated in cluster 1 and cluster 3. Another category is with depth from about 4500 to 10000 ft, which belongs to deep reservoir, and shown in cluster 2, 4, 5, and 6. Each cluster has a quite concentrate ranges for the depth, which means the depth is a main features that distinguished between each cluster. This results is confirmed with the results that we got from the principal component analysis.

Figure 6.6 illustrates the ranges of gravity where most of the clusters have the gravity ranges from about 10 ˚API to 45 ˚API. In cluster 3, we could see that there is a huge number of gravity (90 ˚API), we considered this point is as an outlier because in the dendrogram, this project is cluster 20 with the implementation of steam flooding which this cluster cannot merge with any other clusters for almost all cluster levels. Besides this point, we could find that each cluster is actually represent one king of oil. For example, cluster 1 and cluster 3 are for light oil projects; cluster 5 and cluster 6 are for heavy oil; and cluster 2 and cluster 4 are in between the light oil and heavy oil projects.

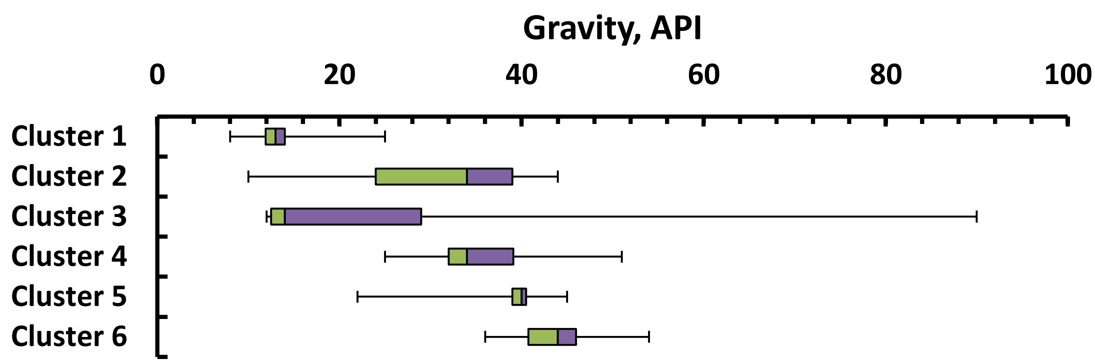


Figure 6.6. Gravity ranges in boxplot for whole EOR projects (from 1996 to 2012 Oil and Gas Journal)

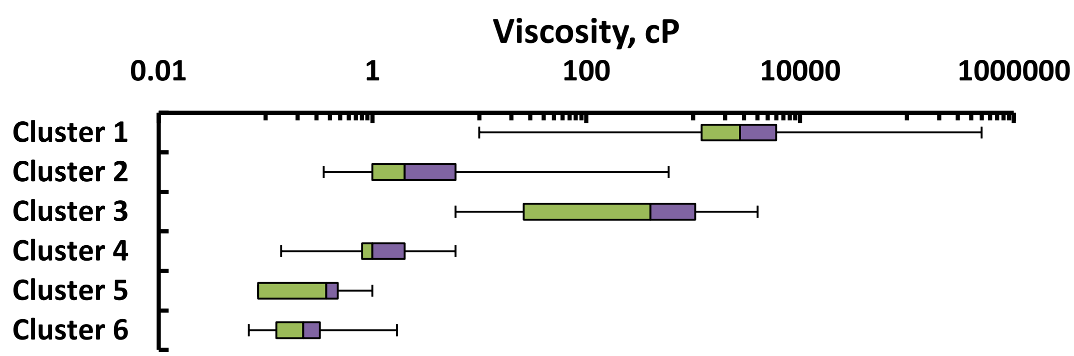


Figure 6.7. Viscosity ranges in boxplot for whole EOR projects (from 1996 to 2012 Oil and Gas Journal)

Figure 6.7 represents the ranges of viscosity for each cluster. The overall ranges of viscosity is from 0.02 to about 70000 cP. In cluster 2, 4, 5, and cluster 6, they are indicating the projects with extremely low viscosity, which is just about 1 cP. On the other hand, cluster 1 represents all the projects with high viscosity (bigger than 10000 cP), and the main range for cluster 1 is from 200 cP to 6000 cP. Cluster 3 shows the projects with intermediate viscosity, which is about 20 cP to 1000 cP.

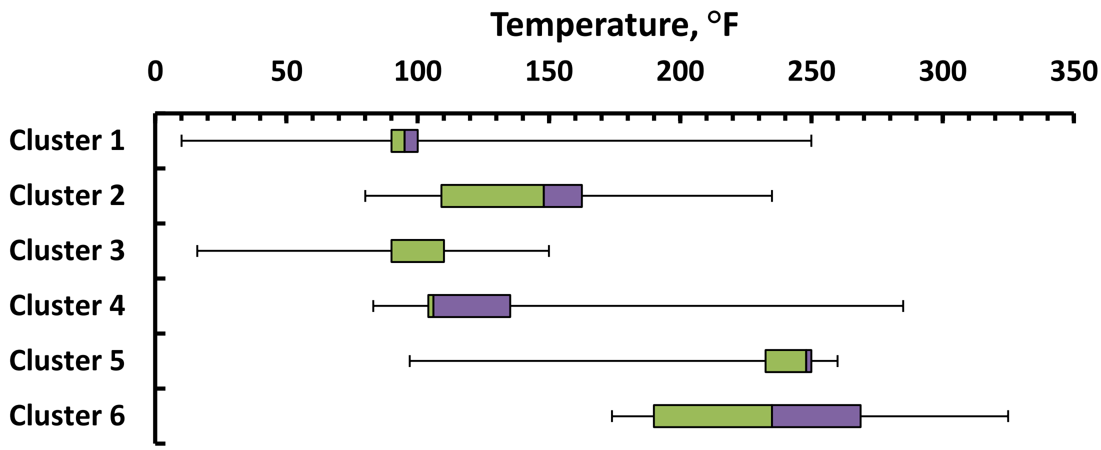


Figure 6.8. Temperature ranges in boxplot for whole EOR projects (from 1996 to 2012 Oil and Gas Journal)

Figure 6.8 shows the temperature ranges. Besides cluster 5 and cluster 6, the range of first 4 clusters are pretty close, which means the temperature distance between these four clusters are very small. On the other hand, cluster 5 and cluster 6 have quite high temperature, the distance between these two clusters is small but quite big with the first four clusters.

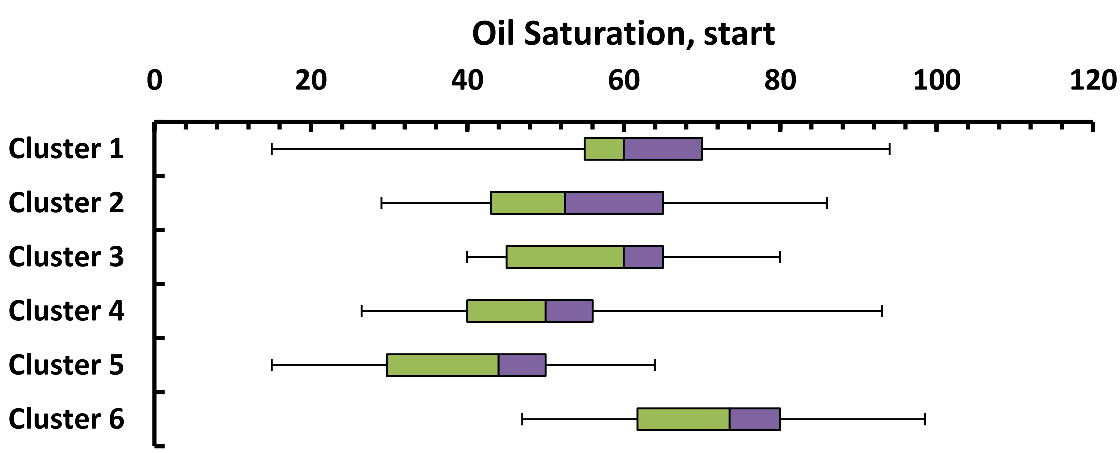


Figure 6.9. Oil saturation at start ranges in boxplot for whole EOR projects (from 1996 to 2012 Oil and Gas Journal)

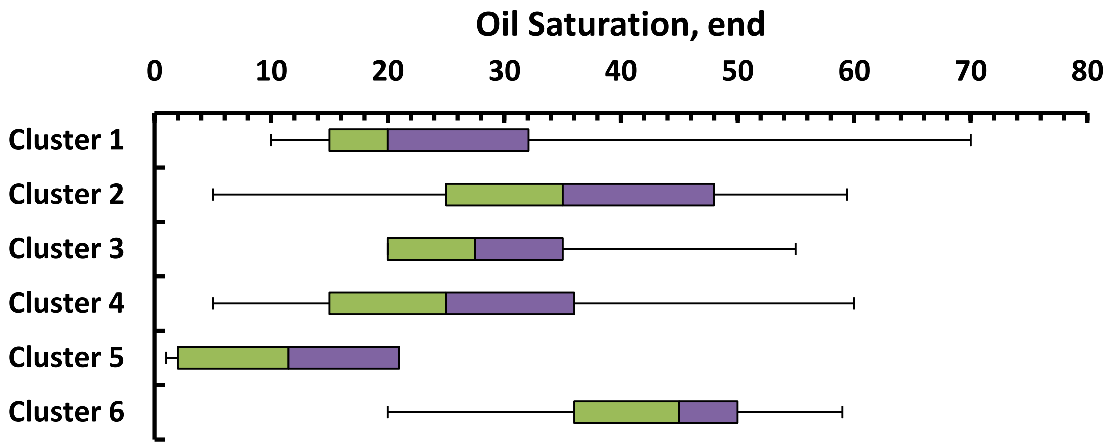


Figure 6.10. Oil saturation at end ranges in boxplot for whole EOR projects (from 1996 to 2012 Oil and Gas Journal)

Figure 6.9 and Figure 6.10 illustrate the ranges of oil saturation before and after the application of EOR techniques, respectively. The overall ranges of oil saturation at start is from 15 to 100, while the overall ranges of oil saturation at the end is from almost 0 to 70. This information indicates that the oil saturation decreases a lot after the implementation of EOR techniques. One more thing we could find is that cluster 1 is the cluster which drops the greatest amount of oil saturation after EOR methods.

6.3. PRINCIPAL COMPONENT ANALYSIS

Figure 6.11 is the mono plot for whole EOR projects. As the mono plot explanation illustrated in Figure 4.7, in this figure, the three dominating reservoir parameters are still permeability, depth and viscosity, which are the same as what we got from the steam flooding projects. In this mono plot, the length of these three reservoir parameter vectors are almost the same. However, the relationships indicated in this plot are different. In the whole EOR projects, permeability is a little bit correlated with the viscosity, and depth is negatively correlated with permeability and viscosity, respectively. The rest of the reservoir parameters (gravity, porosity, temperature, oil saturation start, and oil saturation end) have way less importance compared with the three parameters depicted before. The reason for this might be the unimportant parameters are more dependent with permeability, depth, and viscosity, while permeability, depth, and viscosity are the three attributes that are more likely to be independent to other reservoir parameters and they are more representative. Meanwhile, the three main attributes have less missing values in the data set, which indicates that they have higher data quality.

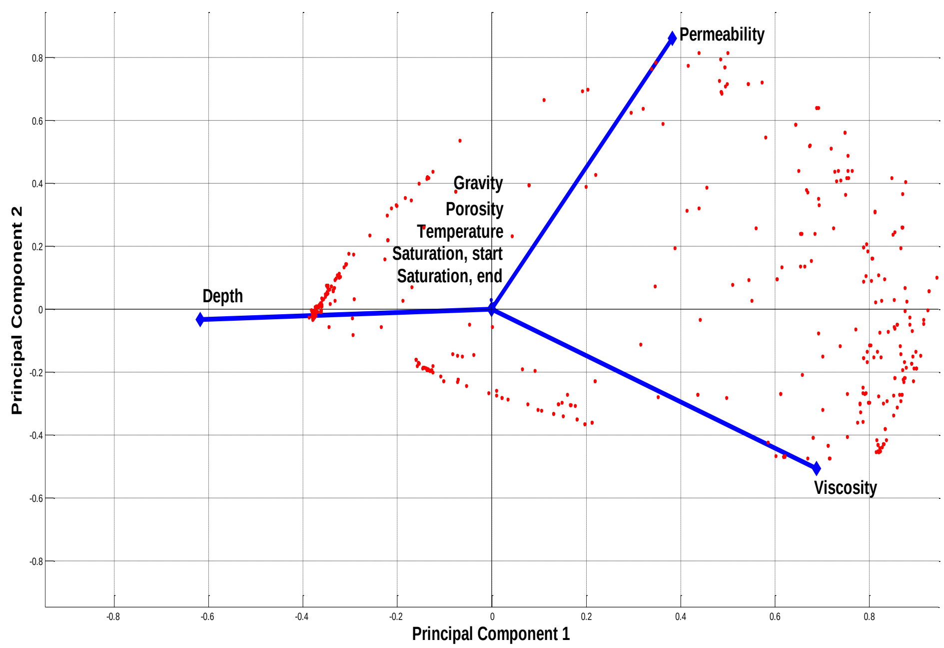


Figure 6.11. Mono plot for whole EOR data set (from 1996 to 2012 Oil and Gas Journal)

In Figure 6.12, the first principal component retained 76% of the variance while the second principal component retained 17% of the variance, which 93 % of the variance were retained by the first two principal components in the whole EOR data set, which satisfied the requirements mentioned in the literature review (90%). Therefore, this 2D scatter plot is a good representation of clustering result. Moreover, each cluster is clearly distinguished each other, in the other words, each cluster falls into a specific area (eclipse), which confirms with the results that expected by implementing clustering algorithm.

Therefore, principal component analysis was an useful and successful approach that were utilized to find the main attributes in the data set, also to present all the projects in a way that people are able to compare the differences and the locations of each projects.

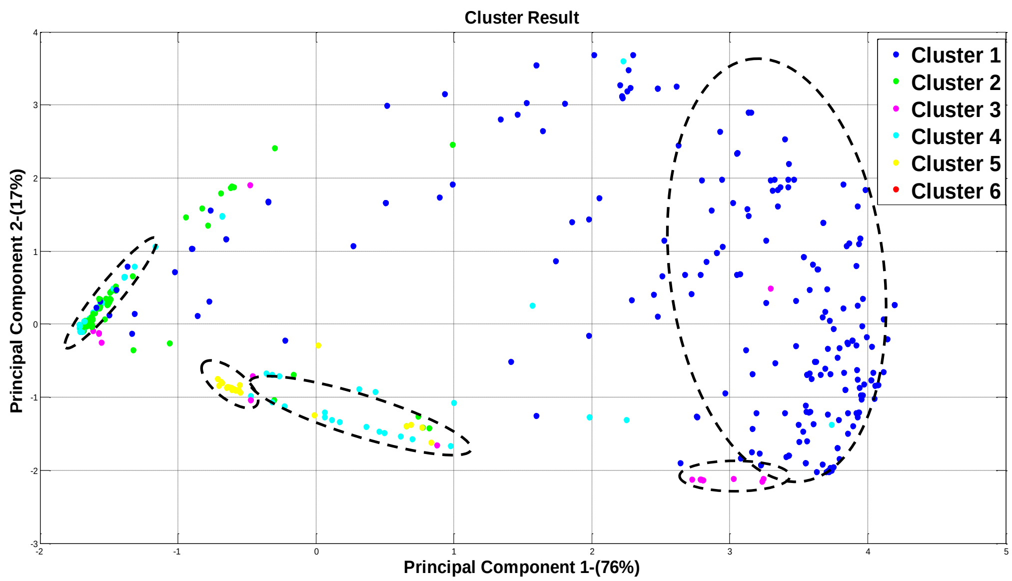


Figure 6.12. Whole EOR projects clustering results with 6 clusters (from 1996 to 2012 Oil and Gas Journal)

6.4. VALIDATION AND EOR PREDICTION

6.4.1. Validation. In order to test the effectiveness of the hierarchical clustering method to the whole EOR data set, the study of validation methods is also used in this research.

This research established the methodology for the validation purpose to study the effectiveness of the established methodology, which mainly including four steps, as illustrated in the Figure 6.13 below:

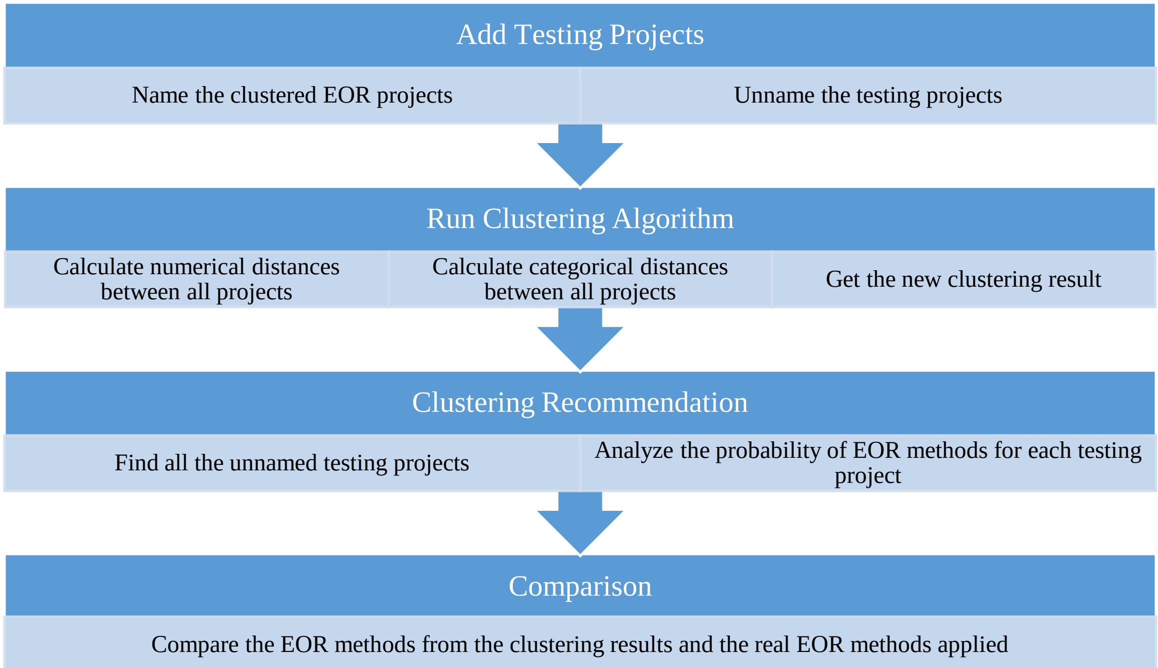


Figure 6.13. Validation process

Step 1: Add testing projects into the clustered whole data set. In this step, each project is assigned a cluster name from Cluter 1 to Cluster n based on previous clustering result, except the new added tesing projects. For example Cluster 1, Cluster 2, Cluster 3, etc.

Step 2: Run clustering algorithm for the updated data set, which includes both the new testing projects and the original EOR data set. This process calculate the distance between all the projects including both categorical data and numerical data. Each testing projects will merged with the projects into a common cluster if they share the similar properties. The output of this process is the new clustering results with n clusters.

Step 3: Clustering recommendation. Find the unamed testing projects from the clustering results, and figure out the best recommended EOR methods for each testing projects based on the clustering result.

Step 4: Comparison. This process is the most important step for validation, which is by comparing the recommended EOR methods from clustering and the EOR methods applied for each testing projects practically.

30 new testing projects were implemented by using the established clustering algorithm methods. Table 6.3 below presents one of the output of one testing projects out of 30 from the program. It clearly shows that the last row is the new project, which the EOR methods applied in that reservoir is unknown at the beginning. However, by looking at the details of this cluster, it is easy to find that all the named projects (previous projects) coincidentally applied the CO2 miscible flooding technique in this cluster (Cluster 5). Hence, the cluster results will recommend CO2 miscible flooding is the only and the best candidate for this testing project, which is correct from the 2014 EOR Survey.

Table 6.3. Cluster validation for one testing project

Type Object	**Formation**	**Porosity**		**Permeability**		**…**	**Cluster #**
		min	max	min	max		
		%	%	md	md		
CO2 miscible	S	23	23	30	30		Cluster 5
CO2 miscible	Tripol.	23.7	23.7	4.5	4.5		Cluster 5
CO2 miscible	S	24	24	700	700	…	Cluster 5
CO2 miscible	LS	25	25	85	85		Cluster 5
CO2 miscible	S	29.5	29.5	2000	2000		Cluster 5
New	**S**	**17**	**17**	**30**	**30**		**CO2 miscible**

As the validation result shown in Table 6.3, the new project falls into Cluster 5, with coincidentally all the old projects in Cluster 5 were the implementation of the CO_2 miscible flooding method. Hence, CO_2 miscible flooding is the only and the best candidate for the new project, which is correct from the 2014 EOR Survey. Table 6.4 below illustrates all the results for 30 testing projects. All the testing projects are successfully fall into the cluster that it belongs to, and 29 out of 30 projects are predicted correctly. Therefore, the established hierarchical clustering algorithm, along with the cluster results are able to indicate and recommend the candidates for a new, unknown EOR projects.

Table 6.4. Cluster Validation for 30 Testing Projects

Project #	**Related Cluster #**	**EOR Type**	**Result**
1	5	CO2 immiscible	X
2	13	CO2 immiscible	√
3	1,3,14	Nitrogen immiscible	√
4	7	Chemical, polymer, surfactant	√
5	6	Chemical, polymer, surfactant	√
6	2	CO2 miscible	√
7	5	CO2 miscible	√
8	12	Hydrocarbon miscible	√
9	6	Hydrocarbon miscible	√
10	11	Hydrocarbon miscible	√
11	11	Hydrocarbon miscible	√
12	11	Hydrocarbon miscible	√
13	12	Hydrocarbon miscible	√
14	12	Hydrocarbon miscible	√
15	11	Hydrocarbon miscible	√
16	11	Hydrocarbon miscible	√
17	11	Hydrocarbon miscible	√
18	11	Hydrocarbon miscible	√
19	11	Hydrocarbon miscible	√
20	11	Hydrocarbon miscible	√
21	11	Hydrocarbon miscible	√
22	11	Hydrocarbon miscible	√
23	11	Hydrocarbon miscible	√
24	11	Hydrocarbon miscible	√
25	11	Hydrocarbon miscible	√
26	11	Hydrocarbon miscible	√
27	1	Steam	√
28	1,3,14	Steam	√
29	1,3,14	Steam	√
30	1	Steam	√
Predict			30/30
Success			29/30

6.4.2. EOR Prediction. As mentioned before, the intension for this thesis is to help reservoir engineers and companies to figure out the best candidate for a particular reservoir. In this section, methods for EOR prediction will be presented, which is the cluster center method.

The input data consists in a simplified description information of the target reservoir, which includes the data ranges for both reservoir properties and fluids properties. The cluster center method is a prediction method of EOR projects by comparing the center of clusters with the new project(s). If we input a new project, the program will compute the distance between the new project and the existing cluster centers, which is the average value of each features. So 6 cluster centers were computed in total. However, there are two categorical features in the whole EOR data set, and it is difficult to compute the cluster center for categorical features. To solve this problem, the numerical distance of cluster centers for the 6 clusters were calculated first, then all the combination of EOR methods and formation types existed in the cluster were listed, then apply the corresponding numerical distance clustering center to each combination. In other word, for each cluster, the value of numerical reservoir parameters is the average value in that cluster, and for the categorical features, all the combinations are listed, and each combination have the same numerical values because they are still in the same clusters. Therefore, instead of just have one cluster center, several cluster centers have been used to represent all the combinations of data for one cluster.

Table 6.5 below illustrates the cluster centers for cluster 1 with parts of the numerical features. Because in Matlab, it automatically generated an ID in sequence to represent the location of the project in the data set, cluster ID was assigned for each cluster centers which is the same with the ID generated in Matlab, so this helps to understand the outputs from Matlab much easier.

Table 6.5. Cluster centers for cluster 1

Cluster ID	**cluster #**	**Categorical Features**		**Numerical Features**			
		Type object	Formation	min Porosity %	max Porosity %	…	…
1	1	Steam	S	32.00533	32.12533		
2	1	Combustion	S	32.00533	32.12533		
3	1	Hot water	S	32.00533	32.12533	…	…
4	1	polymer	S	32.00533	32.12533		
5	1	Steam	US	32.00533	32.12533		

Figure 6.14 illustrates all the cluster centers used before EOR prediction. As illustrated before, the cluster center IDs for cluster 1 is from 1 to 5. It is clear laid out that those five cluster centers still merged into the same cluster, so does the rest 5 clusters. Therefore, even though there are multiple cluster centers for each cluster, the cluster centers for the trained whole EOR projects still keep same.

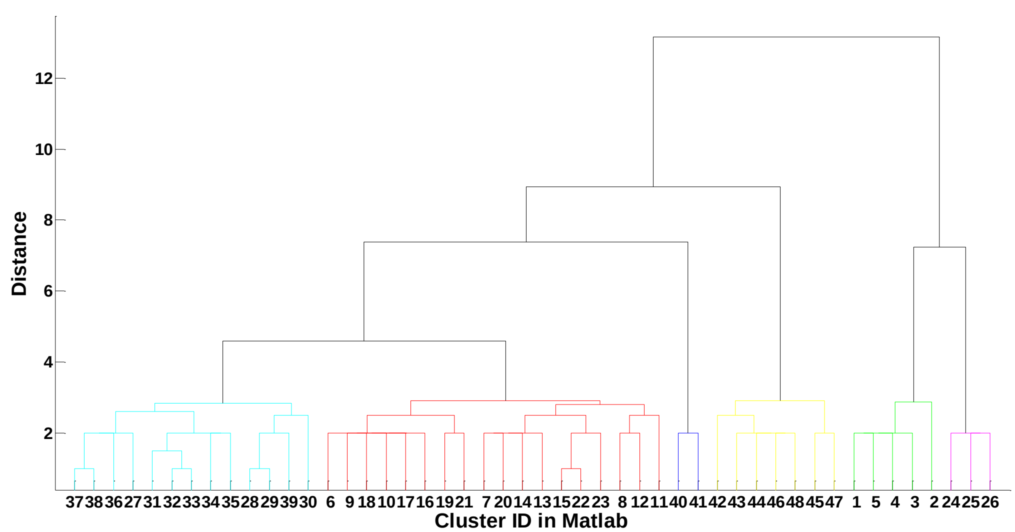


Figure 6.14. Clustering centers

Next is to compare the similarities with the center of each cluster. The closer the new project with one center of the cluster, the more possibilities of the new project share the same reservoir characteristics with the cluster, which means the new project has the potential to use the same EOR method(s) that the cluster used.

Figures 6.15 to 6.17 show the prediction results for the input of 1 new project, 10 new projects, and 30 new projects, respectively. Table 6.6 compared all the results from prediction.

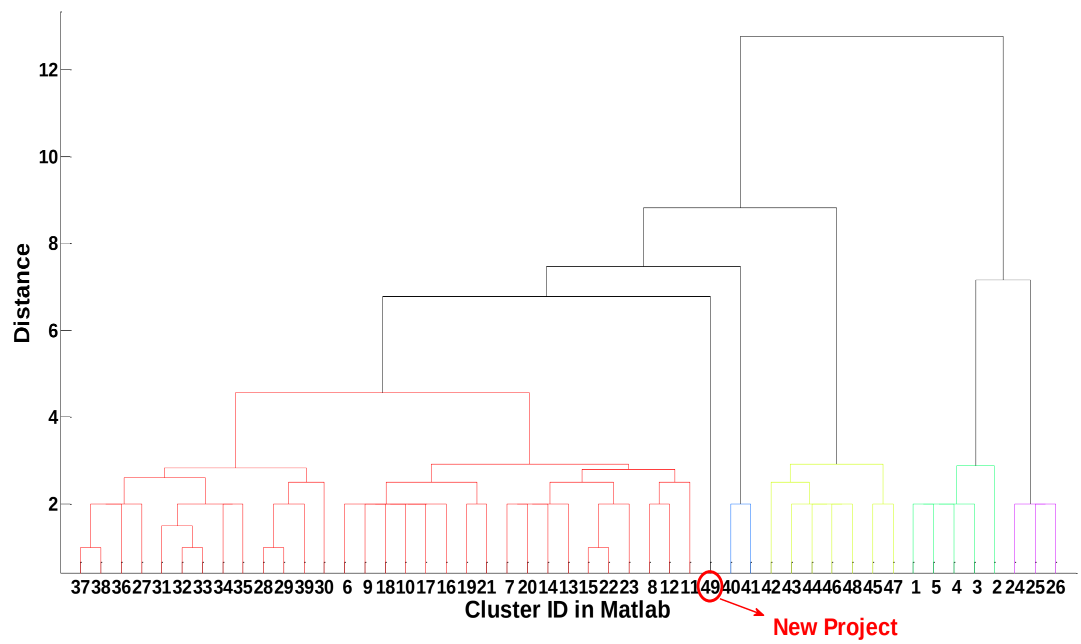


Figure 6.15. Results with 1 new project

Figure 6.15 shows that the new project formed a new cluster during the prediction process, which indicates that this new project is not close enough to all the established cluster centers. The reason for this is because the existing cluster centers all share the same numerical values if they were in the same cluster, however, the new project just has itself and do not share any value with other clusters, that makes the new project an unique one and formed a new cluster itself.

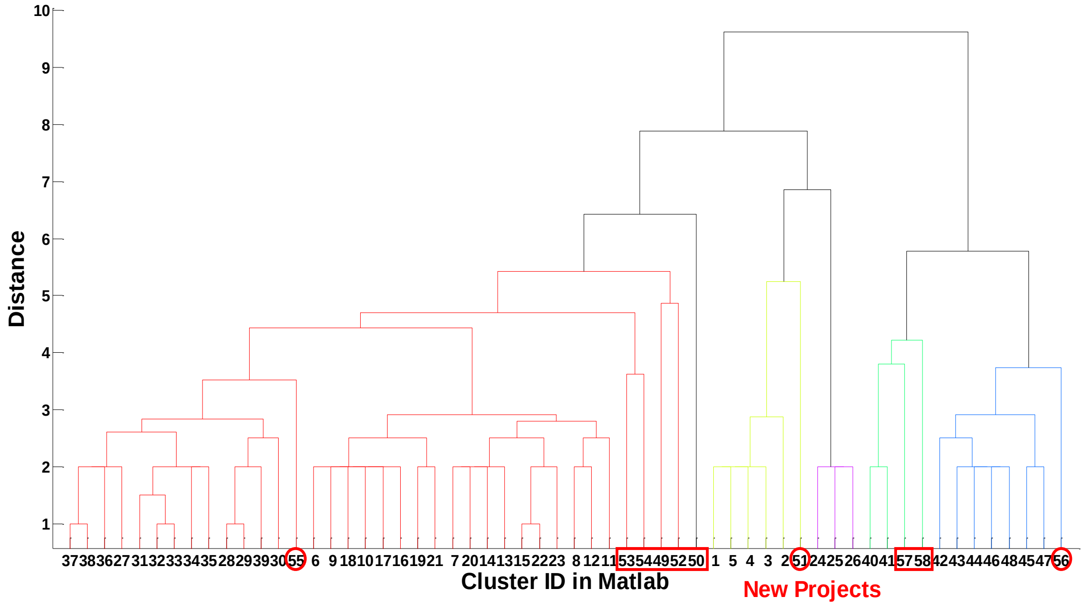


Figure 6.16. Results with 10 new projects

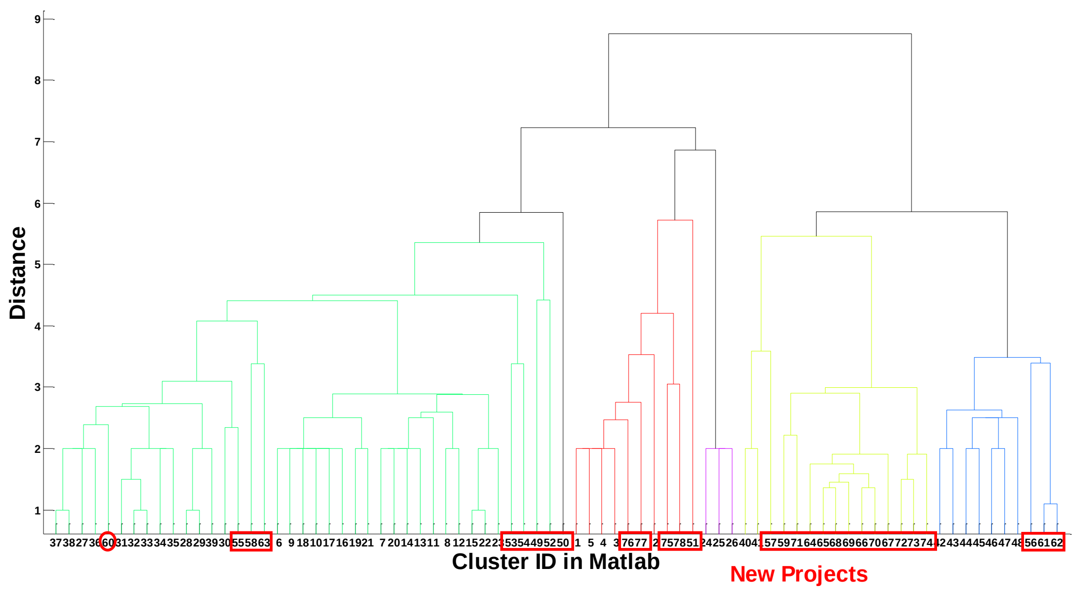


Figure 6.17. Results with 30 projects

However, from Figures 5.16 and 5.17, more projects were able to predict by using the cluster center method. With the increase of prediction project numbers, both the predictability and accuracy were increased.

Table 6.6. Prediction results

Cluster #	**Record # in Matlab**	**Single project**	**10 projects**	**30 projects**
Cluster 1	1-5		51	76, 77, 75, 78, 51
Cluster 2	6-23			53, 54, 49, 52
Cluster 3	24-26			
Cluster 4	27-39		55, 53, 54, 49, 52	60, 55, 58, 63
Cluster 5	40-41		57, 58	57, 59, 71, 64, 65, 68, 69, 66, 70, 67, 72, 73, 74
Cluster 6	42-48		56	56, 61, 62
new		49	50	50
Predict		0/1	9/10	29/30
Success		0/0	5/9	20/30

The black numbers in Table 6.6 shows the projects has been predicted correctly, and the red numbers represent that the prediction results was wrong. As the table illustrates, this prediction method is not good if the prediction project is just one, single projects, in this case, the validation process could be used to get the rough recommendations of EOR methods because one projects will still form the same structure of the clustering results while obtaining high accuracy of prediction success. However, high accuracy of prediction success could be achieved if a larger number of projects need to predict.

Tables 6.7 to 6.12 illustrates the percentage of the possible EOR methods in each cluster, and these tables could help to make the prediction results much accurate if several EOR methods were recommended as candidates.

Table 6.7. Percentage of possible EOR methods in Cluster 1

EOR Type	**Number of Projects**	**Percentage**
Steam	214	95%
Hot water	7	3%
Combustion	3	1%
Polymer	2	1%
Grand Total	**226**	**100%**

Table 6.8. Percentage of possible EOR methods in Cluster 2

EOR Type	**Number of Projects**	**Percentage**
CO2 miscible	88	51%
Hydrocarbon miscible	27	16%
CO2 immiscible	20	11%
Polymer/Chemical	10	6%
Nitrogen immiscible	9	5%
Polymer	6	3%
Chemical, polymer, surfactant	4	2%
Hydrocarbon immiscible	3	2%
Microbial	3	2%
Steam	2	1%
Combustion	1	1%
Cyclic steam	1	1%
Grand Total	**174**	**100%**

Table 6.9. Percentage of possible EOR methods in Cluster 3

EOR Type	**Number of Projects**	**Percentage**
Steam	19	95%
Polymer/Chemical	1	5%
Grand Total	20	100%

Table 6.10. Percentage of possible EOR methods in Cluster 4

EOR Type	Number of Projects	Percentage
CO_2 miscible	224	70%
Hydrocarbon miscible	24	7%
Combustion	22	7%
Steam	19	6%
CO_2 immiscible	11	3%
Nitrogen immiscible	7	2%
Polymer/Chemical	4	1%
Chemical, polymer, surfactant	3	1%
Polymer	3	1%
Acid gas miscible	1	0%
Nitrogen	1	0%
Nitrogen & Hydrocarbon immiscible	1	0%
Nitrogen miscible	1	0%
Grand Total	321	100%

Table 6.11. Percentage of possible EOR methods in Cluster 5

EOR Type	Number of Projects	Percentage
CO_2 miscible	56	92%
Steam	2	3%
Chemical, polymer, surfactant	1	2%
Combustion	1	2%
Nitrogen	1	2%
Grand Total	61	100%

Table 6.12. Percentage of possible EOR methods in Cluster 6

EOR Type	Number of Projects	Percentage
Hydrocarbon miscible	9	53%
Nitrogen immiscible	3	18%
Nitrogen miscible	2	12%
Nitrogen & Hydrocarbon immiscible	1	6%
Polymer	1	6%
Polymer/Chemical	1	6%
Grand Total	17	100%

7. CONCLUSIONS

Results from the application of hierarchical clustering to the steam flooding and worldwide EOR data set demonstrated the effectiveness of the approach to group data into different clusters, and each cluster has different characteristics by using box plots and bar charts. Based on the clustering results, screening criteria for steam flooding projects with detailed analysis have been established based on categories, instead of the overall ranges of a set of reservoir and fluid properties typically obtained in traditional screening criteria studies. Inconsistent data is quickly filtered out into small clusters, which have 1-2 records mostly.

Principal component analysis techniques are really helpful to analyze the data, present the clustering results, and also to figure out the dominating features in both the steam flooding projects and the worldwide EOR data set. The dominating features are permeability, depth and viscosity for both data sets.

From the validation and prediction of the established method, a rapid with high prediction accuracy method have been used which could save valuable time for decision making, especially for mature reservoirs.

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